Mika Aalto

AGENT-BASED MODELING AS PART OF BIOMASS SUPPLY SYSTEM RESEARCH

ACTA UNIVERSITATIS LAPPEENRANTAENSIS 858

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Dissertation for the degree of Doctor of Science (Technology) to be presented with due permission for public examination and criticism in the Auditorium of Mikkeli University Consortium, Mikkeli, Finland on the 14th of June, 2019, at noon.

Acta Universitatis
Lappeenrantaensis 858

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ISBN 978-952-335-382-4
ISBN 978-952-335-383-1 (PDF)
ISSN-L 1456-4491
ISSN 1456-4491

Lappeenranta-Lahti University of Technology LUT
LUT University Press 2019

Abstract

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Lappeenranta 2019
66 pages
Acta Universitatis Lappeenrantaensis 858
Diss. Lappeenranta-Lahti University of Technology LUT
ISBN 978-952-335-382-4, ISBN 978-952-335-383-1(PDF),
ISSN-L 1456-4491, ISSN 1456-4491

Interest in the use of agent-based modeling (ABM) for studying biomass supply systems has increased because of its flexible and cost-efficient nature. While ABM has been around for a long time, recent developments in computing technology and modeling software have enabled more capable and complex models. This powerful dynamic simulation tool permits studying complex systems that feature interaction elements.

Simulation-based study can be used to support decision-making and increase understanding of the supply-system mechanisms involved with the various sources of biomass and the various technologies for utilizing it. While the modern use of biomass is often considered carbon-neutral and pressure to limit greenhouse-gas emissions has led the European Union to encourage this use, activities related to biomass supply systems may still cause greenhouse-gas emissions, so it is important to plan the system well and take dynamic elements into account. There are several complicating factors: supply systems are often considered complex systems, and biomass, with its variations in supply and demand, low energy-density, and high impact of transportation on usage costs, is a challenging study subject of a highly dynamic nature.

Accordingly, the possibilities and challenges of using ABM for studying biomass supply systems were assessed. The current use of simulation, especially ABM, was evaluated by means of bibliographic analysis with regard to three distinct modeling methods. Practical use of ABM in biomass supply chain study was examined with three models, which differed in geographical scale and level of abstraction: a model focusing on effects of policy changes, one centered on applying Big Data for simulation purposes, and a model integrating simulations with Geographical Information System data and ABM.

ABM was found to display the method-related problem of disparate terminology and reporting methods. There have been advances toward greater commonality in term use and efforts to standardize reporting, but uniform practice must be achieved before awareness and interest can grow. Also, while ABM proved to be good at handling large datasets and was able to generate huge result sets, their careful analysis is required if the conclusions are to be correct. Toward this end, however, some solutions involving design of experiments have been offered as a tool to select scenarios that better reveal the causes and consequences of the relevant events.

ABM's good handling of data and its cost-efficient, flexible, and fast scenario analysis prove it to be highly suitable as a biomass supply system research tool. Models' credibility and usefulness in this field is especially important because academic research uses simulation methods as a form of prototyping that may be used to focus study on certain scenarios, producing more precise results in line with real-life applications.

Keywords: Dynamic simulation, simulation, decision-making, forest biomass, individual-based model

Acknowledgements

This work was carried out in the Laboratory of Bioenergy at Lappeenranta-Lahti University of Technology LUT, Finland, between 2015 and 2019. I want to thank my supervisor for giving me the opportunity to join the team. I want to also thank him for valuable guidance, support and comments for my thesis. I received support from all persons in the team and I want to thanks all of them. Especially co-author Mr. Olli-Jussi Korpinen, who participated in all articles, helped me with GIS related problems and tolerated me and my humour.

Many thanks for the reviewers, Dr. Peter Rauch and Dr. Dimitris Athanassiadis, who gave valuable comments. Not only did thay tell me what was wrong in my thesis, but thay also give new insight in the subjects evoking better discussion and reasoning in the thesis. Thank also for all the co-authors of the Publications for they work, as they did make it possible to assemble this study.

Deepest gratitude goes to my wife, Mrs. Armi Aalto, who have helped me with linguistic problems, but also supported me all the time. She had patience to allow me to work this thesis, but also made me take a break when needed. Although, my son was much better at forcing breaks in my schedule and I thank him for all the distractions.

Final thanks goes to all the persons who have supported and guided me during this journey. Thanks to my parents for support, friends for offering downtime and all personnel at Mikkeli University Consortium (MUC) who participate coffee breaks and peculiar talks at Kettukahvila (Coffee room at MUC).

During the journey of making this thesis, many frightened me by telling it will be long, laborious and stressful. For comfort, they told me it will be worthwhile. I admit it to being worthwhile, but it was also fun. Just doing one part at a time, the workload was moderate and time just flew by. It was only solving the problem and moving on. Although, sometimes you do not succeed, but not giving up makes it a question if the subject is more stubborn than you. I still have not found such a subject.

Mika Aalto
June 2019
Mikkeli, Finland

For Santtu,
my son

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List of Publications

Publication I
Aalto, M., KC, R., Korpinen, O-J., Ranta. T. (2018). Modeling of Biomass Supply System by Combining Computational Methods –A Review Article. *Applied Energy*. 243. pp. 145–154.

Main author. Concluded bibliometric analyses and participated at all stages of preparing the paper and wrote most of the paper.

Publication II
Korpinen, O-J., Aalto, M., Venäläinen, P., Ranta. T. (2018). Impacts of the High-Capacity Truck Transportation System on the Economy and Traffic Intensity of Pulpwood Supply in Southeastern Finland. *Croatian Journal of Forest Engineering*. 40(1). pp. 89–105.

Planned the structure and developed the simulation model used in the paper and participated planning of the study. Helped with the analyses of the results and preparation of the paper.

Publication III
Aalto, M., Korpinen, O-J., Ranta. T. (2018). Achieving a Smooth Flow of Fuel Deliveries by Truck to an Urban Biomass Power Plant in Helsinki, Finland – an Agent-Based Simulation Approach. *International Journal of Forest Engineering*. 29(1). pp. 21–30.

Main author. Developed the simulation model used in the paper and conducted the analyze of the results. Participated at all stages of preparing the paper.

Publication IV
Aalto, M., Korpinen, O-J., Ranta. T. (2017). Dynamic Simulation of Bioenergy Facility Locations with Large Geographical Datasets - A Case Study In European Region. *Bulletin of the Transilvania University of Braşov*. 10(59). pp. 1–10.

Main author. Developed the simulation model used in the paper and conducted the analyze of the results. Participated at all stages of preparing the paper.

Publication V
Aalto, M., Korpinen, O-J., Ranta. T. (2019). Feedstock availability and moisture content data processing for multi-year simulation of forest biomass in energy production. *Submitted in Silva Fennica*.

Main author. Developed the simulation model used in the paper and conducted the analyze of the results. Participated at all stages of preparing the paper.

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Nomenclature

ABM	Agent-based model/modeling
CHP	Combined heat and power
DES	Discrete-event simulation
DOE	Design of experiments
DTS	Discrete-time simulation
FMI	Finnish Meteorological Institute
GIS	Geographical information system
HCT	High-capacity transport
iLUC	Indirect land-use change
LCA	Life-cycle assessment
LiDAR	Light detection and ranging
LULUCF	Land use, land-use change, and forestry
ODD	Overview, Design concepts, and Details
OR	Operations Research
WoS	Web of Science

1 Introduction

1.1 The motivation for the research

Biomass has aroused interest as a substitute for fossil fuels in various energy-related sectors. This is due to biomass being considered as sustainable and renewable energy source and with correct use carbon-neutral. Biomass shows great versatility in its potential applications to produce electricity, heat, and biofuels for the transportation sector. Studies have concluded that biomass offers the potential to be a large contributor to the future energy supply (Field et al., 2008; Wasajja and Daniel Chowdhury, 2017; Demirbas et al., 2009). Although biomass holds potential to mitigate environmental problems linked with fossil fuels, there remain challenges, among them environmental ones. The net effect of the biomass depends on what biomass is used, the technology that is used to convert it, and whether the usage of the biomass is sustainable. Also, policy changes generate challenges, as seen with Directive (EU) 2015/1513 of the European Parliament, intended to reduce indirect land-use change (iLUC). Land use, land-use change, and forestry (LULUCF) regulation takes carbon stocks into consideration when addressing greenhouse-gas emissions. Biomass presents economic challenges too. Because of the low energy-density, logistics factors have a great impact on the costs associated with biomass, stemming from the resultant need for large storage areas and the high transportation costs (Ranta et al., 2002; Sikanen et al., 2016; Rentizelas et al., 2009).

Supply systems are often considered to be complex systems, because multiple elements operate in interaction with the environment and each other (Rentizelas et al., 2009). Furthermore, complex systems are frequently nonlinear, with feedback loops, adaptation issues, and uncertain elements. A biomass supply system has hot-chain aspects in addition: sometimes, two entities have to be in the same place at the same time, lest one have to wait for the other, wasting time and causing unnecessary costs.

With its numerous, very different applications and means of utilization, biomass is challenging to study. Since there are many possible way to utilize biomass, each with unique challenges, one must use a study method that is flexible, cost-effective, permits working with multiple scenarios, and can take into account uncertainty. There are several types of computational modeling methods available that meet these criteria, but most have limitations when applied to multiple objects interacting in a spatial environment with temporal variations. Agent-based modeling (ABM) and related simulation have been described as forming a flexible dynamic simulation method that may be used in combination with data from geographic information systems (GIS) to handle spatial variation (Becker et al., 2006; Borshchev and Filippov, 2004). That said, ABM requires an expert to generate the model, and the computing requirements are greater than with some other modeling and simulation methods, such as discrete-event simulation (DES).

ABM has many applications, among them studies of market behavior, migration of people, flock behavior, health care, traffic systems, and (of course) supply systems (Sayama, 2015; Borshchev, 2013; Abdou et al., 2012). ABM is a young modeling method, although the first publications that can be described as reporting on it were published relatively early, by Schelling (1971). Today, there are many publications addressing ABM in the study of biomass supply systems (Luo et al., 2016; Moncada et al., 2015; Singh et al., 2014).

Modeling with ABM can be done by pure coding, but there is a wide range of software and toolkits available to aid in the process (Macal and North, 2010; Allan, 2010). Considering ABM a novel approach is justified because current models have the capacity to include more agents, and more complicated models have been developed recently. These have increased the interest in dynamic simulation methods. Researchers' awareness of the potential of ABM is indicated by eight articles published between 2016 and 2018 that report on using ABM to study biomass supply systems, as revealed by a database of peer-reviewed literature, Scopus (Yazan et al., 2018; Mertens et al., 2018; Moncada et al., 2017b,a; Zhang et al., 2016; Luo et al., 2016; Delval et al., 2016; Mertens et al., 2016). The increase in publications may be explained by the greater availability of modeling software and tools today and/or by increased computation power.

Dynamic modeling is a powerful tool that may be used to support decision-making and increase understanding of the mechanisms involved in biomass supply systems. The opportunity to visualize the whole system grants unique insight into system behavior, and, because system changes may be implemented while a simulation run is in progress, effects can be seen quickly. The work reported upon in this thesis was motivated by a desire to examine various ABM use cases for biomass supply system studies and evaluate the advantages provided by ABM features. The features of interest are data-handling, multi-scenario capabilities, scalability in terms of the study region, and use in combination with GIS. Also, challenges encountered in applying ABM for biomass supply system study are addressed and discussed.

1.2 Biomass supply systems

Due to the great variety in types of biomass available and the breadth of technology to utilize it for energy purposes, the European Union has encouraged its use (McCormick and Kåberger, 2007; An et al., 2011). It is important to remember, though, that biomass use may be unsustainable, as in its traditional non-commercial use with very low efficiency (Goldemberg and Coelho, 2004). With modern use of biomass, the usage itself may be considered carbon-neutral, but other activities involved (e.g., transportation, storage, and processing) may cause greenhouse-gas emissions (Jäppinen et al., 2014). With a well-planned system and sustainable use, biomass mitigates global warming and generates direct and indirect jobs in areas such as provision of energy security (Ragwitz et al., 2009).

In light of ABM, challenges of biomass supply systems are presented and how future policies and technology advantages makes simulation study methods more attracting then conventional study methods.

1.2.1 Complexity

Supply-system networks are considered complex systems on account of the many interactions, with multiple operators – of several types – in the network. The network has to adapt to internal and external changes at short notice, and effects ripple through the entire network. This illustrates the highly dynamic nature of the network. These points are noted also by Surana et al. (2005), in terms of supply-system networks' similarity to complex adaptive systems.

The complexity of a biomass supply system is evident from Figure 1.1, where production, logistics, and supply-systems management are presented (Marques et al., 2012). Marques et al. (2012) identified more than 100 information types in this context during a brainstorming meeting. These were grouped into 22 relatively independent information entities, given such names as Harvesting Unit, Forest Operation, Transformation Center, Wood Yard, Forest Product, Supply Plan, and Forest Inventory.

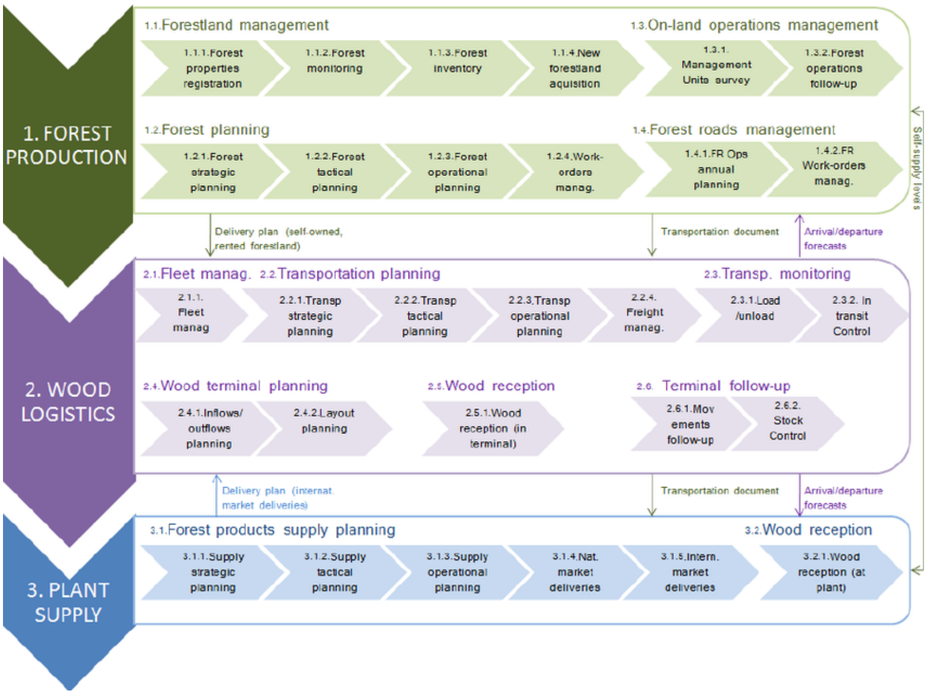


Figure 1.1: Architecture framework of the wood supply system process. The main process types are forest production (1), wood logistics (2), and plant supply (3) (Marques et al., 2012).

In addition there are external factors affecting the system. One external factor is the weather. Demand varies widely with weather conditions. This is especially problematic in cold areas such as the Nordic region, where demand peaks in wintertime. Supply too is affected by the weather: in the long term, crop and forest growth rates are influenced by climate, and shorter-term effects of the weather on supply include matters of road access (heavy machinery may cause damage to the roads if the conditions are not suitable for it).

1.2.2 New policies and technologies

Biomass supply systems are experiencing change as new policies and technologies are implemented and higher demand is generated, in both new and existing locations. One example of new policies and machinery in Finland involves permitting high-capacity transport (HCT) trucks' use for transporting materials (Venäläinen and Korpilahti, 2015). An example of new technology in forest biomass supply systems is the Kesla C 860 H hybrid wood chipper (Laitila et al., 2015). These are only a couple of examples, from a dozen technologies that have already been demonstrated in Europe (Alakangas et al., 2015). These new technologies change the behavior of the system, so studies and research have to be done before they are introduced to the supply system. Studying only new equipment does not show how it affects material flows downstream or information flow upstream.

1.3 Agent-based modeling and simulation

Terminology in field of simulation is challenging, especially with ABM that have terminology still developing. Commonly used terms in this thesis are defined and processes behind terms are explained in section 1.3.1. Also characteristics of ABM are presented and explained.

1.3.1 Definition of model, simulation and ABM

A model, in this context, is computer representation from a real-life system or event. One approach is to think of a model as a digital prototype that lives in the computer. The entire model needs to be validated and verified before it is used to conduct studies. The term "modeling," which refers to developing the model, covers creating the model and doing all the verification and validation work. Finally, "simulation" denotes using the model. It may seem that all modeling and simulation are naturally separate tasks, but debugging and updating the model is carried out by modeling and simulating in parallel. Sometimes, the term "agent-based modeling and simulation" is used in discussion of ABM.

Defining agent-based modeling precisely is challenging since the modeling assumptions are wide open (Sayama, 2015). Sayama (2015) sum up ABM in one sentence thus: “Agent-based models are computational simulations models that involve many discrete agents.” Challenges of describing ABM were part of a panel discussion (Siebers et al., 2010) in which it was noted that, by the strict definition of its attributes, true ABM does not exist in operations research (OR). Instead, OR uses a combination of DES and ABM. Agents are defining difference as ABM uses active entities, that have particular attributes and interact with each other and the environment (Abdou et al., 2012; Bandini et al., 2009) and DES use more passive entities that move through system and instigate and respond to the events (Schriber et al., 2014). Agents allow data stored inside them making possible to carry information or use large data set to generate multiple agents with own unique properties.

1.3.2 Characteristics of agent-based model

Simulation-based study methods differ in their properties, with certain characteristics specific to each simulation method. The traits of ABM are its stochastic, dynamic, and discrete system model. A visual presentation of the various system models’ characterization is given in Figure 1.2, where ABM is in the bottom right (Leemis and Park, 2006).

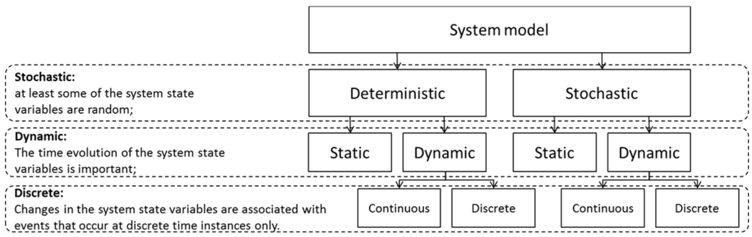


Figure 1.2: A diagram of the characterization of a system model, via a typology (Leemis and Park, 2006). Agent-based modeling is at the bottom right.

In an approach with a stochastic character, the model may use probability distributions as values, allowing the model to include randomness. Among the situations for which this is advised are various delay-linked events (such as loading and unloading times, travel time, and servicing time) but also events connected with entities’ arrival schedules – the results may be more realistic if arrival events’ intervals are randomized. Including stochastic events in the model makes it more realistic since these events are not constant in real life, and stochastic values may be used if there are no experimental data available for base assumptions. Use of stochastic values does make the model more complicated and renders it more difficult to have repeatability in the model. For good probability distributions, the work must use large datasets from real-world measurements with solid statistical analysis. In some cases, this is not possible and the distribution has to be estimated with reasonable accuracy. In these cases, sensitivity analysis can be conducted to resolve the effect of the distribution on the system.

Being of a dynamic character means that the model takes the time-varying behavior of the system into consideration. The model has to have an internal clock, because it needs to keep track of the time and know what state it is in at particular times. This allows the model to simulate changes in system state, thereby enabling animation of system behavior and obtaining results for different points from the simulation times. In dynamic simulations, the past affects the future.

Characterizing an approach as discrete in nature refers to how time variance is handled in the model. A discrete-time method uses time steps and prompt events base on these time steps. There are two ways of behaving with regard to time steps: synchronously and asynchronously. The former means that events happen only at discrete time steps, and in asynchronous behavior the various events may occur at arbitrary moments, exactly when they are supposed to occur (Borshchev, 2013). Natively, ABM uses asynchronous time, and this is recommended since it lets events happen when they should, making the model appear more continuous. In some cases wherein all events need to take place at the same time, synchronous time steps can be used.

1.3.3 Validation and verification

Validation and verification are conducted to determine how well a model is working. Validation determines whether the model is a reasonably accurate representation of its real-word counterpart (the system or process), and verification ascertains whether the programming of the model is implemented correctly (Xiang et al., 2005; Carson, 1986). There has been considerable discussion of the validation process for ABM, since it is a complicated task and increasing the model complicity may lead to a decline in the validity of the model (Robinson, 2008). Accuracy in stochastic modeling may be tested via sensitivity analysis (Sargent, 2009). Performing multiple runs with the same initial values allows the modeler to see how large an effect stochastics plays in the model. Lorscheid et al. (2012) recommends using coefficient of variation to determine the number of needed repetitions but with a large model this increased work and computing load leading need of lowering repetitions. It is better to run some repetitions than using one result set to do analyze. The same can be done with initial values, by changing one value and carrying out sensitivity analysis. Thus, the modeler may detect whether one value has a huge impact on the results, and illogical result sets from sensitivity analysis can reveal problems with the model. Another validity-test method is to compare simulation results with data from real-world experiments, but this is in some cases challenging or even impossible. After all, simulation studies may well be done for a system that does not actually exist.

1.3.4 Use of agents

ABM focuses on agents that have their own parameters and are able to interact with each other and with the environment, making judgments on how to act on the basis of the situation. Since all agents have their own parameters, each agent may be unique, but in some situations several agents have unifying features. These agents constitute a population or collection such as a truck fleet or the demand points. Although some properties are the same, there may be unique values within the population, such as different truck payloads or demand-point locations, respectively. This population or collection of agents creates the possibility of having numerous agents and easily controlling them as a group.

In addition to individual-specific parameters, an agent may have unique functions, states, events, or triggers for events. Forming individual agents and creating behavior is a bottom-up approach. At the bottom are the individual agents and the actions that they take. Through interactions with others and the environment, the subsystem is generated, and, in turn, interactions with subsystems generate the system that is studied (Sayama, 2015). In contrast to a top-down approach, such as that in DES, a system overview is describable but details are omitted or subsystems are refined until the desired level of detail is achieved (Varga, 2001; Zeigler et al., 2000).

There are many interactions in a biomass supply system – involving, for instance, the available supply and the transport machinery delivering feedstock to the demand point. These interactions can be described because all operators in the system may be regarded as agents in the model. Since there are large amounts of information exchange in the system, agents have to communicate with each other and react to the situation at hand. There are also environment changes that affect the system.

Modeling of the biomass supply system proceeds from aim of study and study boundaries to the understanding of the system that is embodied by the model. Determining the factors and what results the model should be provided with before development of that model begins is called conceptual modeling (Robinson, 2008). This process is carried out multiple times in the course of development of the model, as shown in Figure 1.3. Creating the model begins with the general idea to be actualized, and the scope, level of detail, and representations of the model are reviewed and change as understanding of the system and model becomes established. As it is not possible to model everything, so simplifications and abstractions have to be made. Simplification changes complex logic more simpler (ex. generating feedstock at one time when in reality it should accumulate over time) and abstraction is level of detailing (low abstraction have maximum detailing and high abstraction minimal detailing).

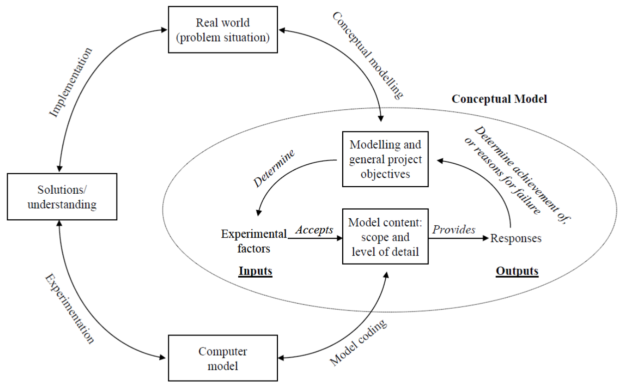


Figure 1.3: The conceptual model in the simulation project life cycle (Robinson, 2008).

1.4 The focus of the thesis

Various biomass supply system studies have been conducted by means of a simulation-based study method, such as DES (Lee et al., 2002; Mobini et al., 2011; Zamora-Cristales et al., 2014; Windisch et al., 2015; Eliasson et al., 2017) or ABM (Krishnan, 2016; Zhang et al., 2016). As ABM gains popularity, it is important to look at the specific challenges and possibilities it brings with regard to a biomass supply system in particular. New technology advantages offered by improved modeling software and computer performances allow the use of new methods and also combinations of information sources, such as modeling from an online dataset alongside real-time data.

The main research question of this theses is how ABM can be used in the biomass supply system studies and what benefits it offers? To answer this question, current use and future prospects of ABM in the area of biomass supply system studies are explored. While it is clear that ABM has been used for studying supply systems, exactly how and why this is done today is less obvious. To determine this, bibliometric analysis was conducted, for Publication I. In that analysis, several scientific articles published before 2017 that report on either ABM or DES were addressed, besides GIS and life-cycle assessment (LCA) publications. The publication also discusses studies that have combined various methods and what terminology has been used in the papers reporting on these.

Use of ABM for supporting decision-making is commonplace, and the flexibility of the agents makes it possible to study the effects at several spatial scales and operation levels. Publications II and III study if ABM can be used to to study the effects of policy on different spatial and operator scales. Publication II addresses various effects of a new policy in Southeast Finland, which allows larger-payload trucks to operate in the region. This policy's particular effects on local operators were examined in Publication III, through a model focused on a combined heat and power (CHP) plant yard and applied to studying how the higher-payload trucks and the equipment used in the yard influence the trucks' flow.

Information and data are available in larger and larger quantities, and ABM is a data-centered study method. The quantity and precision of the data depend on the abstraction and structure of the model. The modeler may leave establishment of some values for the user of the model. To demonstrate how big data and GIS may improve ABM studies, Publication IV shows how a large body of data may be used for regional studies, and Publication V presents a data-preprocessing method for a multi-year simulation model.

Because studying a complex system such as a biomass supply system network with such a flexible and complex method as ABM leads to models that have numerous agents, functions, and events, guaranteeing that the study method is scientific necessitates transparency and repeatability. This may be challenging. The discussion in the thesis addresses the need for complexity, and the problem of excessive complexity is reviewed in light of today's large-scale availability of data. This discussion takes note of the terminology issue and of the importance of consistent, uniform terminology both for, initially, identifying studies that use a given method and also for understanding and applying one's own contribution to advance the field of computational modeling as a scientific study method. Also considered is the notion of validation, along with the importance of it.

ABM is well suited to supply-system studies, and it offers valuable information for decision-making that is impossible or at least extremely challenging to acquire by using traditional study methods. Publications III and IV show that ABM may be used for systems that are in the planning phase, and Publication II demonstrates its use to study changes in an existing system. In both cases, all analyses were done without affecting operative actions, and multiple scenarios were processed, to produce extensive knowledge of the various effects that could arise from the numerous possibilities of the decisions.

The discussion here is focused more on the modeling than on the results of the simulations to bring up challenges of using ABM. The purpose of this thesis is to show different methods for studying biomass supply systems and to discuss the challenges and solutions in agent-based modeling. Special attention is devoted to combined use: the advantages of GIS use are considered, and the possibility of using LCA is discussed. The benefits of using ABM as study method for biomass supply system are shown in the publications, and additional contributions for future researches is discussed.

2 Materials and Methods

2.1 Bibliometric analysis of three modeling methods (Publication I)

Bibliometric analysis was conducted for ascertaining how three computation methods have been combined. These methods were GIS-based ones, LCA, and either DES or ABM as discrete-time simulations (DTS). The analysis was conducted by means of headwords (see Table 2.1) that characterize the biomass, supply system, and methods. These headwords were then compiled into search queries to find articles published before 2018, for all methods. Two scientific databases were searched, the Thomson Reuters Web of Science (WoS) and Elsevier's Scopus. Any article returned for two methods was reviewed, for seeing how the methods were combined and what challenges and advantages their combination represented.

Table 2.1: Headwords of the queries.

Description of biomass	Description of Supply chain	Description of method
Biomass	"Supply chain"	**GIS**
Bioenergy	"Supply system"	"Geographical information system"
Biofuel	"supply network"	GIS
Bioethanol		"Spatial analysis"
Biodiesel		"spatial statistic"
biogas		
"Energy wood*"		**LCA**
"Forest fuel"		"Life cycle assessment"
"wood chip*"		LCA
woodchip*		"Life cycle analysis"
"Wood waste"		"Lifecycle assessment"
"Pellet*"		
"Energy Crop*"		**DTS**
"sugarcane"		"Agent-based"
"Agricultural waste"		"Discrete-event"
"Municipal solid waste"		"multi-agent simulation"

The searches were for headwords in the keywords, abstract, or title that matched the query conditions. To address the possibility of authors using a different term or only a subclass when describing a study, headwords were constructed in three classes, as shown in Table 2.1. The headwords in a given class were combined via the "OR" Boolean operator. For inclusion in the search results, one or more headword needed to be found. The classes were combined with the "AND" Boolean operator, to guarantee having at least one headword found for each class. Also, the search queries used an asterisk so that alternative suffixes would be included in the search results. Because the search engine adds the "AND" operator if space is left between words, exact phrases were supplied in quotation marks.

The search queries were constructed on the basis of the databases' instructions, and then the searches were carried out. In total, six queries, three for each database, were constructed for the searches. The articles found were listed and compared, for identification of those referencing two or more methods. Analysis of the papers focused on how the combining was done and what challenges rise from using multiple modeling methods.

2.2 Agent-based models for testing the effects of policies

Policies are set to guide decisions and effects on a system so as to achieve the desired mode of action. For Publication II, the effect of a policy that allows HCT trucks to operate along predetermined routes in Finland (Venäläinen and Korpilahti, 2015) was studied at regional scale via ABM construction using a routing network of HCT corridors and the road network with an HCT terminal option for the supply system. Publication III reports on testing the effects of the same policy from a power plant operator's perspective by means of ABM that uses dynamic layout and changeable yard equipment.

2.2.1 Region scale (Publication II)

To test the effect of HCT trucks' use in road-based roundwood transport, the agent-based simulation model SimPulp was developed. The model focuses on impacts to the costs and transportation distances of replacing part of a standard truck fleet with HCT vehicles. The case study was conducted for the part of Finland where pulpwood use is the most intensive. The HCT vehicles were assumed to face limitations in accessing roadside storage areas and to have to rely on transshipment terminals, to which regular trucks bring wood from roadside storage.

The transshipment terminal locations considered and the proposed HCT corridors are shown in Figure 2.1. In all, 14 HCT terminals were positioned at highway intersections on the basis of visual examination of the routes of the regular trucks to the supply points as revealed by GIS data. In the model, the demand for the wood was generated by seven pulp mills in the area. Supply was generated by 491 centroids of a 5 × 5 km grid that represents roadside storage. Annual supply was estimated based on pulpwood harvest in Finnish municipalities, and amounts were allocated to the various supply points on the basis of GIS analysis. Supply from outside of the study area was generated at the transit points.

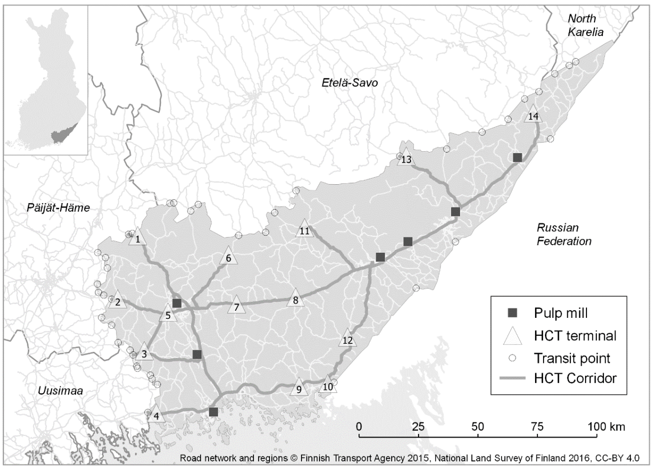


Figure 2.1: The network of trunk roads in pulpwood transportation, pulp mills, potential HCT terminal locations, HCT corridors, and transit points between the study area (in gray) and the surrounding area.

The model judges supply at the start of the day in light of annual supply allocated from the given supply point and the distribution of the relevant wood types. When a supply point has generated enough for one truckload, that point offers the wood type in question to the demand points. Ordering of the offering is determined on the basis of unit costs for the relevant route, and offers are made both for following direct routes to the demand point and for going via the terminal route. The demand point accepts a direct offer if it has room in on-site storage, and the "via terminal" option is accepted if there is room for the wood at the terminal. The sizes of the on-site and terminal storage areas are determined by annual demand. If the accepted route is via a terminal, a standard-type truck is reserved to transport the wood to the terminal, where the wood is stored until the demand point accepts it from the terminal and an HCT truck is available to transport it to that demand point. At the start of the day, the terminal offers wood before supply points to the demand point, to keep the circulation of stored material high. This allows terminals to be used as off-site storage. Trucks are simulated only when they are at work; i.e., journeys to the truck park, maintenance time, and driving needed for driver change are omitted from the simulation.

The costs of the transportation are estimated with equations that were fitted on the basis of HCT trials between October 2014 and September 2017 by Metsäteho. Costs have two parts: distance base costs as how long distance truck drives and time based costs as how long time trucks spend for transportation. The effect of the costs of terminal operations is tested with €0/ton, €0.50/ton, and €1.00/ton. The costs of each transportation journey are recorded at the demand point and added up at the end of the run. The route that a vehicle takes is recorded to gather information on the road usage. Other information of interest is the usage of the terminal and any unfulfilled demand that arises on account of the stochastic nature of the model. To minimize the effect of stochastics, eight simulation runs are conducted for replication, and the average of the results is used in the analysis. In all, 82 scenarios were generated, varying in the number of terminals in use, total transportation capacity, and the proportion of HCT vehicles (see Figure 2.2). These scenarios were qualified on the basis of accumulated shortage in the demand points: if the total shortage amount ended up too large, the scenario was disqualified and omitted from the considered result set.

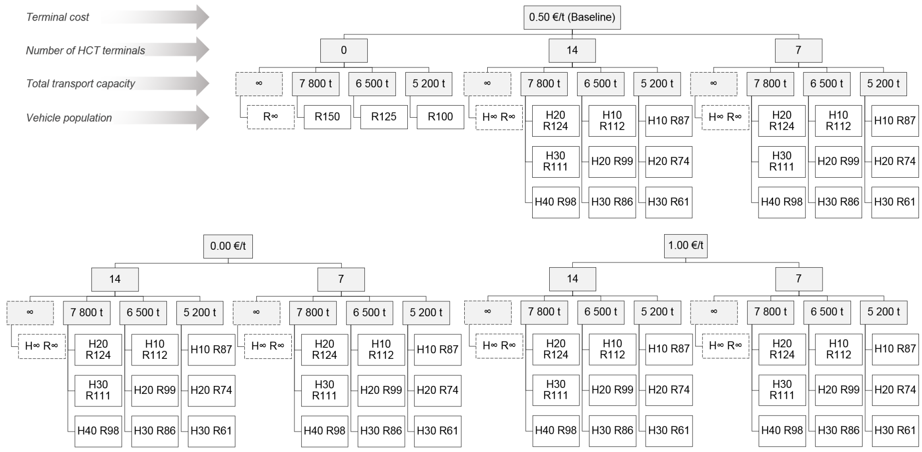


Figure 2.2: The configuration of the simulation scenarios (fields in white). Items with a non-broken outline indicate qualified scenarios. Fields with a dashed outline indicate reference scenarios with an unlimited vehicle count. H = number of HCT trucks, and R = number of regular trucks.

2.2.2 Operator scale (Publication III)

The higher capacity of wood-chip trucks for energy production affects the number of trucks arriving at the power plant but also the equipment at the yard. With the district-heating plants being located near urban areas, land area is valuable. That leads to power plant yards that are smaller and more tightly packed with equipment. This limits the amount of equipment and the room for trucks to turn, wait, or unload. The challenge increases when a new plant is being planned or when plant capacity is increased. Addressing such issues, the study for Publication III used ABM to consider plant yard operations with various truck fleet compositions and machinery sets in the yard space.

The environment modeled was a plant yard that was constructed from lines and points. Lines between points were used for distances and average driving speed between points. This layout setting lets the user change the yard structure by generating a new look to the layout that abstracts from the details of the real structure in the presentation of the environment, as shown in Figure 2.3. This setup allows one to study several yard layouts with the same model, but the user must perform validation of the layout for every setup to ensure layout being realistic and as intended. The model limits layout structure by forcing the trucks to visit the weighing station as they are arriving but also when they depart. If two scales are in use, the truck has to use the same one for the two weighings.

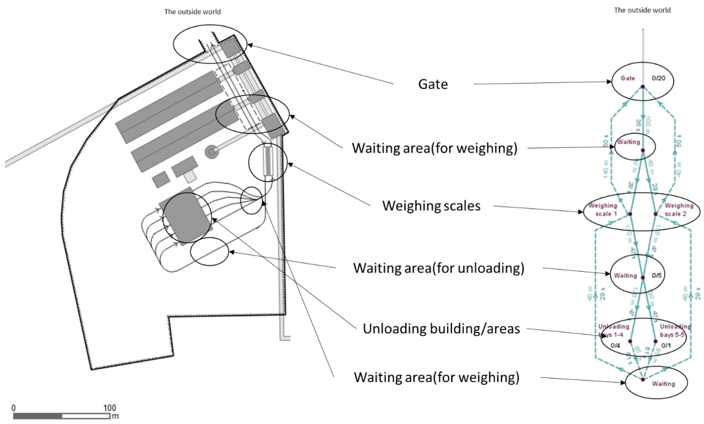


Figure 2.3: The layout of the planned fuel-reception yard and its corresponding representation in the simulation model.

The model uses queue theory. Although such models could possibly be made with DES as Väätäinen et al. (2005) have done, ABM was used in order to yield more flexibility for future development such as trucks making decisions based on biomass type and quality they are carrying or include different logics for sampling. In the model, trucks move along the path to the points and, as dictated by the operation, various events are prompted. These events are a delay, waiting for a space, or agents unloading biomass from trucks. The delay time hinges on the properties of the machinery or truck. Delay at the weighing stage depends on the weighing agents' parameters, and the time it takes to unload trucks depends on unloading rate and the capacity of the truck. Trucks' movement through the power plant is presented in the flowchart in Figure 2.4. The number of trucks arriving each day is determined by the truck-type proportions and the demand of the plant.

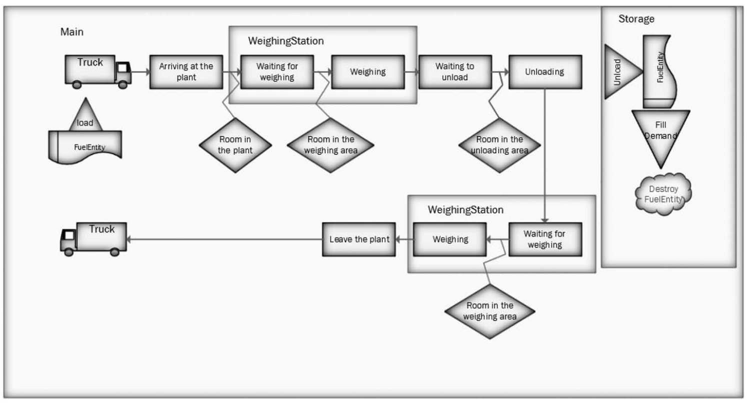


Figure 2.4: A simplified presentation of the process in the model. The rectangles are actions performed by the truck agent, and the diamonds are statements for moving to the next phase. Transparent rectangles represent the agent boundaries, and the triangles show the movements of the fuel-entity agent.

Simulation scenarios were selected to test the effect of the number of weighing stations, the fleet composition, and the sampling method. The scenarios selected were various "S" types, for certain fleet proportions; 1-W, with one weighing station; 2-W, with two weighing stations; AS, with automatic sampling; and MS, using manual sampling. Nine scenarios were studied, in total, and all were run eight times to limit the effect of stochasticity. Since the truck type was selected at random at the start of the trip and was of great importance that types portions were correct in the model, this created a need to conduct sensitivity analysis – the results were rejected if the spread between portions for the runs was too great. The truck capacities used and their proportion in the scenarios are presented in Table 2.2. Simulation time was set to 30 days during winter season, as demand is highest at this period.

Table 2.2: Truck capacities and the capacity proportions for arrivals.

		S 1	S 2	S 3
	Capacity (m^3 loose)	Proportion (%)	Proportion (%)	Proportion (%)
Type 1	140	49	40	10
Type 2	145	31	35	35
Type 3	150	20	25	35
Type 4	180	0	0	20
Total number of trucks	-	53	52	48

2.3 The online material and preparation of the data

Today, large databases are available online, and biomass-related ones have been developed for research purposes (LUKE, 2018a; Datta et al., 2017). This kind of database offers good initial values for use in simulations. That said, databases are often created for multiple users, so inconsistencies may arise, and the format may not be appropriate for use in simulation. Changing the format accordingly and removing unnecessary data are among the preparations needed in preprocessing of the data. Publications IV and V both refer to large online database, but less processing of the data was used for the former, since the abstraction and region level allowed this. Publication V presents a data-preprocessing method that may be used to reduce the amount of abstraction and enable multi-year studies. That publication also considers moisture-prediction models and examines how, with a fairly limited number of experimental results, these may be used in the dynamic simulation modeling.

2.3.1 Large quantities of data in modeling (Publication IV)

For Publication IV, a biomass-availability database covering 37 European countries and several biomass types was used (Datta et al., 2017) to supply availability information for the simulation model. The simulation model, which was used to study eight demand locations, around Europe, uses feedstock-availability and cost values from the database, assigning all demand points their own supply corresponding to the demand point's location. Excessive memory needs to import all regions in the simulation run were circumvented by restricts the model's applicability to one region. The values input by the user does not change base on region. Although it is possible to use the values for multiple demand-point locations, this has to be acknowledged as leading to an understandable deficiency in the results.

A case study was chosen for Publication IV, to demonstrate the model concept and capacity. Eight demand-point locations were selected, all over the European region (see Figure 2.5), and input values, that are same for all locations, were taken from literature that focuses on studies internal to Finland. The model cannot load all countries' databases, since these are prohibitively large, so availability data for only countries with demand locations were imported to the model.

Figure 2.5: Demand-point locations.

The model uses two datasets, denoted as "Primary forest biomass" and "Forest residues," as sources for the feedstock types used. The model employs feedstock-availability estimations for base potential in the year 2020. Primary forest biomass includes stem and crown biomass from felling and thinning, and Forest residues includes residual matter such as brushwood and similar materials. Base potential can be defined as sustainable technical potential, since it takes into account sustainability standards (Datta et al., 2017).

The input values, used for all demand-point locations, are applied for the costs of transporting and processing the feedstock. The database includes harvesting and forwarding costs, but contract costs are not covered. Also, the user needs to specify feedstock properties such as energy value and density. Alongside feedstock provided in line with the database, long-distance transportation offers secondary supply options, with their own properties, which are indicated via arrival tables and costs.

Supply is accumulated from supply points in terms of fuel agents that represent batch of feedstock, and “trucks” agents are summoned to transport fuel agents to the demand point. The comminution of the feedstock is handled at the demand point. Cost information is gathered at fuel agent level, providing the possibility of adding the costs of each operation at the moment the operation is completed. A demand point has a storage area where feedstock is kept before use. Consumption of feedstock is calculated on an hourly basis with the level of demand set by the user. If there is not feedstock to consume, reserve fuel is used. Properties of reserved fuel are based on wood pellets. If terminal use is enabled, trucks may transport fuel agents to terminal, if the storage at demand point is full. There terminal trucks convey fuel agents to the demand point. If the feedstock is taken to a terminal, it is comminuted there, so that it is ready for use at short notice.

In the model, the trucks operate between 8am and 5pm. When a trip is started before 5pm, the truck completes the delivery, from which it returns empty. When there are fuel loads to be collected in the morning, a supply point is selected at random for the trucks, with feedstock availability at the various points being considered as a factor. The truck agent selects the shortest route to the supply point as indicated by routing information. Loading time and the lower speeds on forest roads are factored in by adding a two-hour wait at the supply point.

The feedstock used, the cost of feedstock procurement, and the cost of any reserve fuel used are recorded, and at the end of the simulation these are all exported to a spreadsheet for further analysis. Ten replications are performed for each simulation run for a given demand point, after which simulation for the next demand point is automatically started. In the case study reported upon in Publication IV, eight demand locations were studied, so 80 simulation runs were conducted in all.

2.3.2 Selection and preprocessing of data for modeling (Publication V)

Publication V examines ways to prepare data for a regional biomass supply system simulation model. Data preparation was performed to achieve a multi-year simulation model that encompasses variations in supply points, weather conditions, and changes in biomass quality. To validate the method, supply points for a 2 km $\times$ 2 km grid of the 120 km diameter supply area were generated, and availability of biomass was obtained from the Biomass Atlas database (LUKE, 2018a). This led to a total of 3,883 supply points. Since there are fewer supply points annually available in reality, 200 random points were selected for each year, and a correction factor was applied to the resulting availabilities, as indicated by Equation 2.1.

$$V_{msp,i} = \frac{N_{sp}}{n_{sp}} V_{sp,i} \tag{2.1}$$

In the equation above, $V_{msp,i}$ is the feedstock amount at supply point i in the model and $V_{sp,i}$ is the feedstock amount at supply point i in the initial data. N_{sp} is the total number of supply points (3,883 for Publication V), and n_{sp} is the number of supply point used in the model (200 for Publication V). With this correction, annual supply will be close to databases annual value, although variation will exist, since the supply points are selected at random. To make the repetition of the simulation run possible, the random number generator seed was made possible to be set as an input value.

Data from the database is given as static annual availability and having temporal variation data have to be allocated temporally. Statistical values of harvesting may be used to achieve monthly allocation. Publication IV uses Finland statistical values (LUKE, 2018b) to set the probability of harvesting month for supply points. Harvesting day can be reasonably assumed to be uniformly distributed, although this assumption leaves out the lower working amount of weekends. To test varying of monthly available feedstock and compare it, 30 generations of supply points were created with different random number seed.

Changes in the quality of the biomass were taken into account by estimating the drying of biomass in roadside storage. The estimation possibilities are numerous (Routa et al., 2015; Liang et al., 1996; Erber et al., 2012; Heiskanen et al., 2014; Sikanen et al., 2012; Kanzian et al., 2016). Publication V introduces Routa et al. (2015)'s prediction model (see Equation 2.2, just below) and Heiskanen et al. (2014)'s prediction model (see Equation 2.3).

$$DMC = Coef(evaporation - precipitation) + const \tag{2.2}$$

Here, DMC is daily moisture change; $Coef$ is the net evaporation coefficient, a factor based on storage and wood type; and $const$ is a constant referring to the storage and wood type.

$$w_{i+1} = w_i + a\Sigma P/(w_i - w_{eq} + b) + c\Sigma E(w_i - w_{eq}) \tag{2.3}$$

where w_i is the dry-basis moisture content at time i and w_{i+1} is the value for time $i+1$. w_{eq} is the equilibrium moisture content. P is prescription and E is evaporation between times i and $i+1$. a, b, and c are storage- and wood-type-specific constants, respectively.

Since net evaporation is a factor in these models, one must obtain figures for this rate of evaporation from biomass. Among the possibilities are measured evaporation and use of the Penman–Monteith equation (Equation 2.4) (Monteith, 1981; Allen et al., 1998).

$$\lambda E = \frac{\Delta(R_n - G) + \rho_a c_p \frac{e_s - e_a}{r_a}}{\Delta + \gamma(1 + \frac{r_s}{r_a})} \tag{2.4}$$

Since the Penman–Monteith equation is complicated, it has been simplified by many (Linacre, 1977; Salama et al., 2015; Gallego-Elvira et al., 2012), and for Publication V simplification performed by Linacre (1977) (see Equation 2.5) was tested as one possibility for estimating the evaporation. Using such a simplified equation enables one to apply drying estimates without needing as large a number of measurement results as initial values.

$$E_0 = \frac{700T_m/(100-A)+15(T-T_d)}{80-T} \tag{2.5}$$

Because drying estimations use weather data, this source material has to be acquired. One way to obtain said data is to use values from a weather station near the simulation area. Another possibility is to use open weather data such as the data offered by the Finnish Meteorological Institute (FMI) (FMI, 2011). There are data for specific years, making it possible to apply different weather data for every simulation year. If the simulation is performed for years in the past, correct data for the years in question may be used. Naturally, for simulation of the future, this is not possible. Using random weather data from random years may alleviate this problem, but weather effects still should be examined via sensitivity analysis, to make sure that extreme conditions do not affect the results too much.

3 Results and Discussion of the Publications

3.1 Synthesis of computer modeling methods (Publication I)

For Publication I, the search queries returned, in total, 498 publication on studies using one of the three modeling methods considered, and, of these, 17 combined two methods (see Figure 3.1). No publication that dealt with combining all three methods was found. The distribution of publications between the two databases was even: Scopus returned 152 and WoS 186 unique results and there were 160 publications that were found in both databases. Most publications addressed LCA, and ten of them combined it with GIS and six with DTS. There were one publications addressing DTS and GIS methods combination.

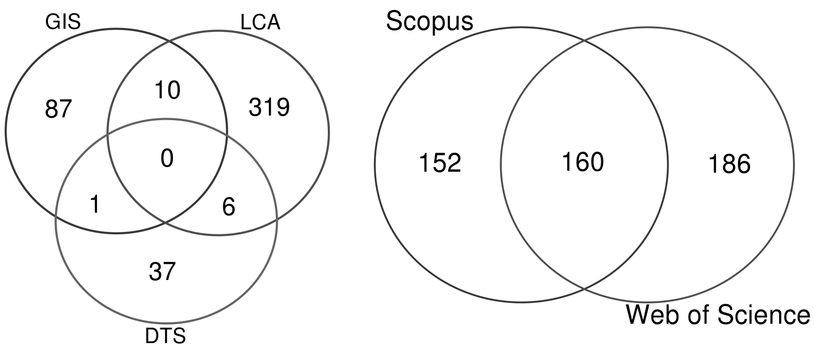


Figure 3.1: A Venn diagram of the publications found.

Analysis results show a rise in LCA publications, which started in 2009 and is still in progress. All modeling methods have gained popularity, although most have done so more slowly than LCA (see Figure 3.2). Among LCA's advantages are its standards for consolidating the procedure, methods, and reporting (Finkbeiner et al., 2006). The publications' extensive distribution over 140 journals indicates that interest in modeling is growing in several research fields.

For LCA, there are standards for how the analysis should be concluded and reported upon. This allows transparent and comparable reporting. A lack of this poses problems for ABM: Different modelers use different terms. This may result in not finding relevant publications or not understanding the method used in a particular model. Automated systems for generating keywords for databases help to avoid this problem, but sometimes the system generates keywords that do not describe a study correctly. This occurred with Zhang et al. (2016)'s study that used multi-agent simulation without LCA: the WoS system added "LCA" via its KeyWords Plus automation. In contrast, with the study by Kishita et al. (2017), WoS added "LCA" for KeyWords Plus. The text of that article indeed used the term "life cycle simulation," or "LCS," so this is a good example of keyword generation working. Two other examples of properly functioning keyword generation are work by Mirkouei et al. (2017) and by Chaplin-Kramer et al. (2017), who used GIS and LCA for their publications.

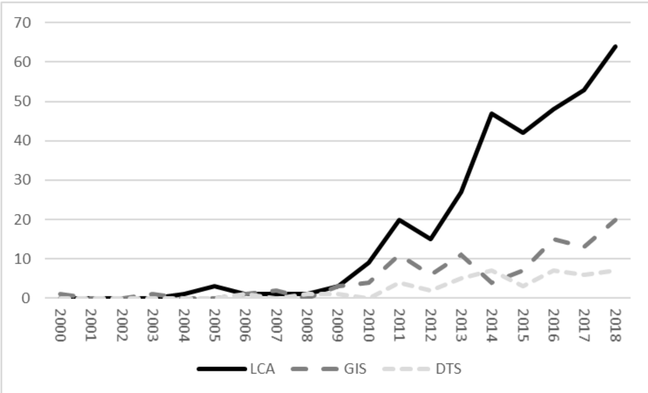


Figure 3.2: Numbers of publications found, by year of publication.

Motivations cited in the publications for combining LCA and GIS methods included adding a spatial aspect to LCA and using GIS data to analyze feedstock availability and transportation networks, for results that can be fed in to LCA. The scholars concluded that the combination of LCA and GIS can benefit decision-makers by offering new information. They also pointed to the importance of taking spatial variables into account in the LCA processes.

One of the key reasons identified for combining LCA and DTS methods was to circumvent LCA's linear and static properties. A combination of LCA and DTS allows conducting dynamic LCA that may handle multi-year studies, consider the effect of different decisions on the environment, and include uncertainty in LCA-based research.

Numerous challenges to combining modeling methods were identified by publications combining methods, for example amount of data, computing load and having coherent assumptions through different models. As all methods use different initial data, combining models demands large datasets. As different types of databases are available, combining methods are more viable, but also models validation against databases improves the validation process. One possibility to lower the amount of needed data is to use assumptions, but these assumptions lower the accuracy of the model and assumptions have to be proper for all models.

As models are combined, the computing load increase excessively. There is a possibility having the models exist in different stages or having the main model detailed while supporting model is less detailed. In some cases the use of mathematical expressions or stochastic distributions to substitute the secondary model would be advised. It is good to notice that some models can be easily integrated into other methods. For example, transportation distances can be calculated by GIS and import to the LCA or DTS model for further analyses.

The increased interest in mathematical computation methods has extended to LCA, GIS, and DTS modeling methods alike. Although combining these methods generates challenges, all the methods have their specific strengths, and these can be used to improve other methods. In some cases, combining methods would be ill-advised and other methods should be employed.

3.2 Simulation of decisions on new policy (Publications II and III)

Publication II is focused exclusively on examining the effect of introducing HCT vehicles to a supply system. The work reported upon in Publication III considered more, different logistics solutions for the planning yard and introduced HCT as one type of the trucks (Type 4). Because the thesis project is focused on the effect of particular policy decisions, focus was directed to the difference represented by HCT scenarios.

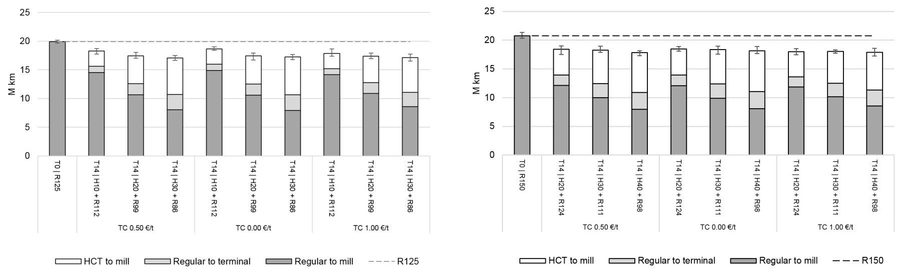
3.2.1 Effects at regional level

For Publication II, 38 scenarios were qualified, from a pool of 82 scenarios in all (see Table 3.1). All 19 scenarios involving 5,200 t total truck capacity were disqualified, indicating that this capacity cannot meet demand. It is worth noting that the figures used for total capacity factored in only the trucks actively working and that, hence, the capacity needed would be higher in real life. Increasing capacity leads to lower accumulation of unfilled demand.

Table 3.1: Fulfilled total demand (FTD) and unfulfilled demand (UFD) for each wood type (format: pine–spruce–hardwood) in the simulation scenarios, where * = reference scenario with unlimited transportation capacity.

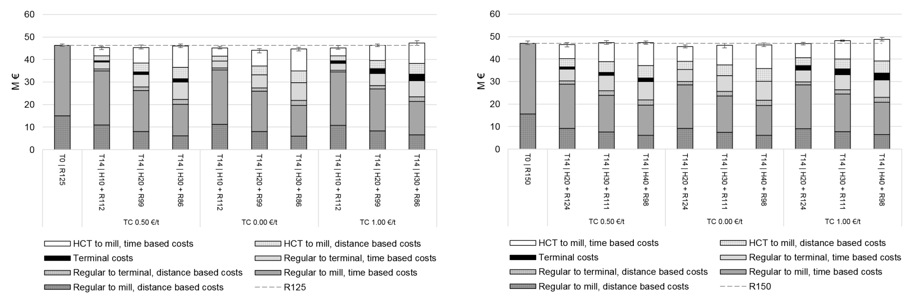
HCT terminals, n	HCT trucks, n	Regular trucks, n	HCT proportion of total transport capacity	Total transport capacity, t	Terminal costs 0.50 €/t (Baseline)		Terminal costs 0.00 €/t		Terminal costs 1.00 €/t	
					FTD, %	Wood type UFD, %	FTD, %	Wood type UFD, %	FTD, %	Wood type UFD, %
-	-	8	-	8	99.0*	0–0–3*				
-	-	150	-	7 800	99.1	0–0–3				
-	-	125	-	6 500	98.6	0–0–4				
-	-	100	-	5 200	(96.1	5–3–4)				
14	8	8	-	8	97.9*	0–1–6*	97.8*	1–1–6*	98.0*	1–1–5*
14	20	124	17%	7 808	98.1	1–1–5	98.2	0–1–5	98.1	0–1–5
14	30	111	26%	7 812	98.1	1–0–6	98.3	0–0–5	98.0	1–1–5
14	40	98	35%	7 816	97.7	1–1–6	98.4	0–1–5	98.1	1–1–5
14	10	112	10%	6 504	98.2	1–1–5	98.4	1–0–4	98.0	1–1–5
14	20	99	21%	6 508	98.0	1–1–5	97.9	1–1–6	98.5	0–0–5
14	30	86	31%	6 512	98.0	1–1–5	97.5	2–1–5	97.6	2–1–5
14	10	87	13%	5 204	(95.1	6–3–5)	(95.6	6–3–4)	(94.9	7–3–6)
14	20	74	26%	5 208	(96.4	4–2–6)	(96.7	4–1–6)	(96.6	4–2–6)
14	30	61	39%	5 212	(90.4	10–9–10)	(91.2	9–8–10)	(88.0	13–12–11)
7	8	8	-	8	97.6*	2–1–6*	98.1*	1–1–5*	97.8*	0–1–6*
7	20	124	17%	7 808	98.3	0–1–5	98.1	1–1–5	98.0	1–1–5
7	30	111	26%	7 812	97.9	1–1–5	98.1	1–0–5	98.2	0–1–5
7	40	98	35%	7 816	98.2	0–1–5	98.0	1–0–6	98.4	0–0–5
7	10	112	10%	6 504	97.8	1–1–6	98.4	1–1–4	98.3	0–1–4
7	20	99	21%	6 508	98.0	1–1–5	97.6	1–1–6	97.6	2–1–6
7	30	86	31%	6 512	97.6	2–1–6	97.9	1–1–6	97.8	2–1–4
7	10	87	13%	5 204	(95.6	6–2–5)	(95.1	7–3–6)	(95.5	6–2–5)
7	20	74	26%	5 208	(96.7	3–2–6)	(96.0	4–2–7)	(96.6	4–2–5)
7	30	61	39%	5 212	(88.9	9–12–13)	(90.3	10–9–12)	(86.5	13–13–15)

Total transportation distance was shorter for all scenarios than in the reference scenarios, and the greatest savings were achieved with the highest proportion of HCT vehicles (as shown in Figure 3.3). The scenario with 6,500 t total capacity featured total transportation distances that were around 3% shorter, on average, than in the 7,800 t scenarios. The transportation costs show a smaller difference. The cost was higher at five scenarios with 14 terminals and lower in 13 scenarios than the equivalent scenario without HCT vehicles (as Figure 3.4 indicates). The variation between replications (denoted by the error bars in the figures) was 0.6–2.6% for these scenarios over an average of eight runs. The most profitable scenario, 20 HCT vehicles and no terminal costs, exceeded the lowest record from scenarios without HCT.



(a) 6,500 t total transportation capacity (b) 7,800 t total transportation capacity

Figure 3.3: Transportation distances, including empty returns, by transportation mode, in scenarios of 6,500 t total truck capacity (a) and 7,800 t total truck capacity (b) with either 0 or 14 HCT terminals. The error bars represent the range of total transportation distances in eight-reproduction simulation runs. H = number of HCT trucks, R = number of regular trucks, T = number of HCT terminals, and TC = terminal costs.



(a) 6,500 t total transportation capacity (b) 7,800 t total transportation capacity

Figure 3.4: Transportation costs, by transportation mode, and their bases, based on scenarios of 6,500 t total truck capacity (a) and 7,800 t total truck capacity (b) with either 0 or 14 HCT terminals. The error bars represent the range of total costs in eight-reproduction simulation runs. H = number of HCT trucks, R = number of regular trucks, T = number of HCT terminals, and TC = terminal costs.

The most economical scenarios with 10 HCT vehicles routed approximately 20% of the wood through terminals, and with 20 HCT vehicles between 34–39% of wood was routed through terminals. Changing the costs of using terminals did not affect total volume but did influence which terminals were used (see Figure 3.5). Terminals 11, 13, and 14 are close to intensive supply, making them attractive locations. Reducing the number of terminals from 14 to 7 pushed the allocation of the supplied material to other terminals, thereby decreasing differences between terminals in this regard.

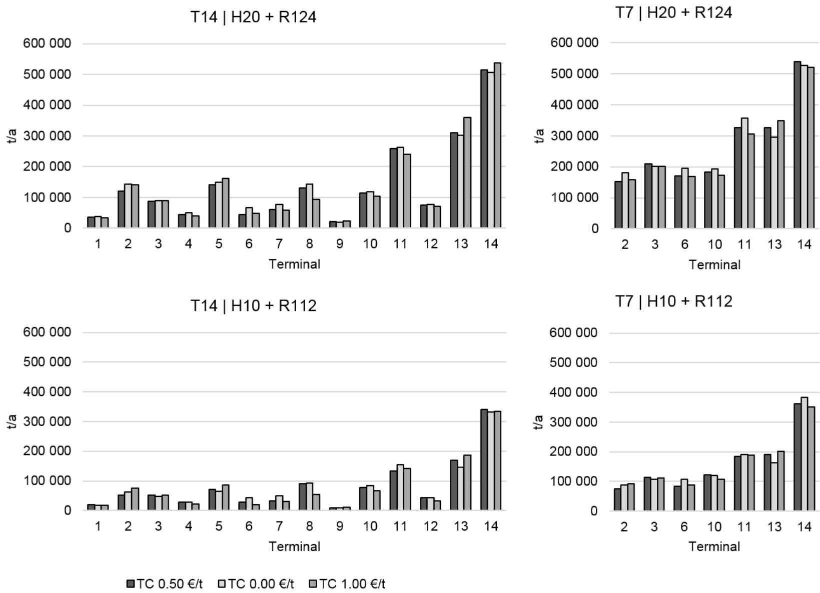


Figure 3.5: Utilization of HCT terminals in 12 HCT scenarios, where H = number of HCT trucks, R = number of regular trucks, T = number of HCT terminals, and TC = terminal costs.

Sensitivity analysis (see Figure 3.6) showed that the most important value affecting total costs was the ratio between HCT vehicles and standard trucks. Scenarios with 10 or 20 HCT vehicles produced around 1.5–2.0% lower total costs than did scenarios with 30 or 40 HCT vehicles or scenarios without HCT vehicles. Sensitivity analysis for the proportional impacts on total costs and trucks' utilization rates indicates that 10 HCT vehicles was not enough to yield a more profitable route than HCT terminals offer.

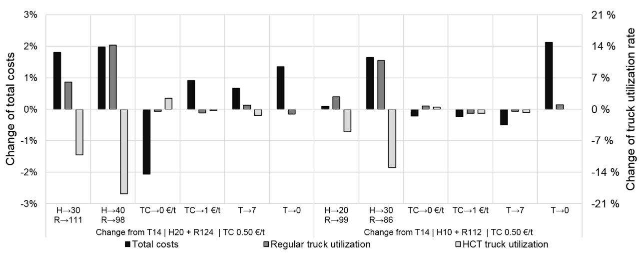


Figure 3.6: Impacts of changes in the truck count, terminal costs, or terminal network on total costs and utilization rates of trucks. Here, H = number of HCT trucks, R = number of regular trucks, T = number of HCT terminals, and TC = terminal costs.

3.2.2 Effects at operator level

Publication III examines the effect of the equipment at the power plant yard and that of differences in the composition of the truck fleet. Scenario 3 introduces HCT to the system by having trucks with 180 m^3 loose capacity in the fleet. Use of HCT vehicles ends up lowering the total number of trucks arriving at the plant, and this leads to less total time being accumulated by trucks at the plant. The higher capacity increases the unloading time in scenario 3, but the waiting times are lower (As waiting times shown in Figure 3.7 indicate).

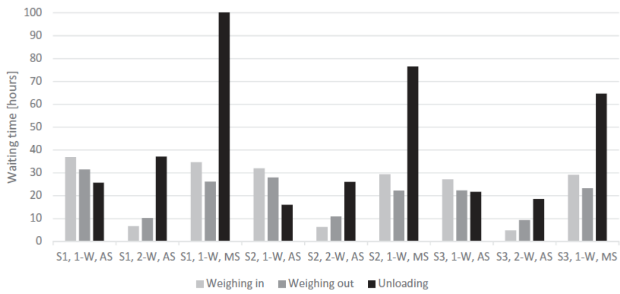


Figure 3.7: The total time that trucks spent in the various waiting areas. The S number denotes the truck proportion scenario, “1-W” refers to one weighing station, “2-W” denotes two weighing stations, “AS” refers to automatic sampling, and “MS” indicates manual sampling.

The effect of times is small at single-truck level, but the effects add up in the course of 30 days. The overall effect can be noticed from Figure 3.8: the trucks spend more than 300 additional hours in the yard with manual sampling than with automatic. The effect of HCT vehicles lowering the total time needed is detectable in scenario 3 using less time in total than do corresponding scenarios 1 and 2. Clearly, the higher unloading time affects the maximum time spent in the yard, with scenario 3 always having a higher time figure than the otherwise equivalent scenarios.

Introducing HCT vehicles to the fleet increases efficiency in the power plant yard by lowering the number of trucks needed for transporting feedstock. This has effects on the various functions in the yard and also reduces truck activity in the area. The latter is important because power plants may well be in urban areas where traffic is already high. There are other ways to alleviate the issue of truck density at the power plant, among them using other transportation types and spacing out the arrival of the trucks. This may be problematic in some cases, though, and adding HCT trucks to the fleet can create its own hurdles, since the vehicles are bigger and heavier. These factors and the associated possibilities have to be considered in case-specific studies.

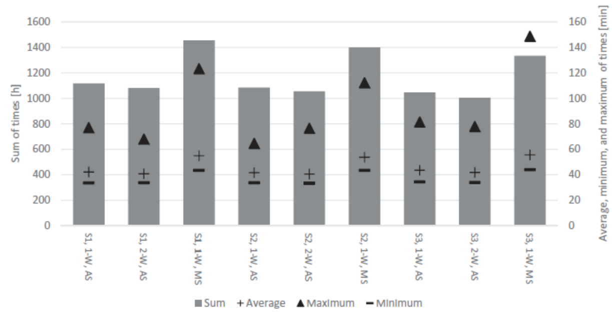
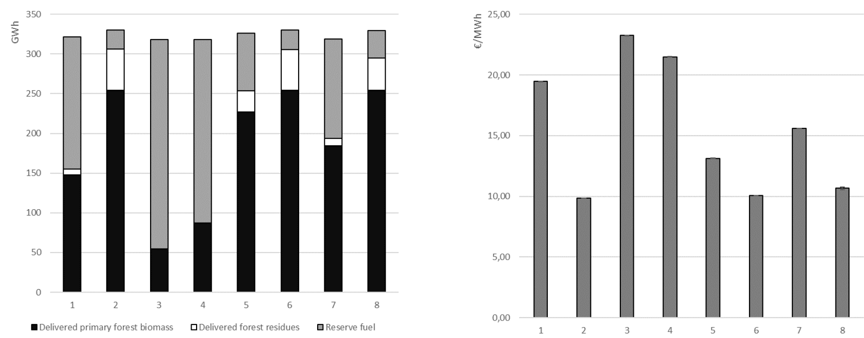


Figure 3.8: The total time that trucks spent at the plant during 30 days at winter. The sum-total time is presented in hours (at left). The average, minimum, and maximum are presented in minutes (at right). “S” denotes the fleet proportion scenario; “1-W” refers to one weighing station, “2-W” to two; “AS” denotes automatic sampling; and “MS” indicates manual sampling.

3.3 Quantities of data in ABM (Publications IV and V)

The setup for Publication IV provided the possibility of studying multiple locations by applying the same initial values for all of them and employing multiple simulations to address alternative scenarios for all demand-point locations. In the paper, two simulation runs are reported upon. Results from the first of these were used to improve the configuration for the second simulation run. The resulting values for feedstock usage are presented in Figure 3.9 (a), from which it can be seen that demand points 2 and 6 have the highest biomass use. These locations are in Austria, and the third-highest biomass-use figure was found for Romania’s demand point 8. High use of biomass also led to the lowest costs for obtaining feedstock, since the reserve-fuel price was set to be high in the relevant scenarios (see panel b in the Figure 3.9). High use of biomass also necessitated high storage capacity, over 60,000 m^3 (loose) in some cases.



(a) Feedstock use

(b) Feedstock costs

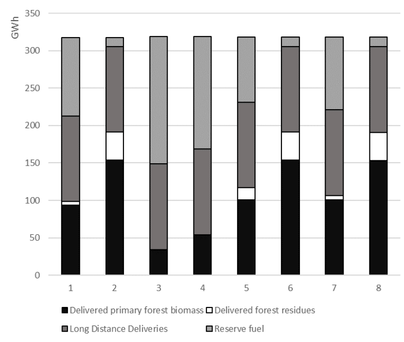
Figure 3.9: The distribution of feedstock use and costs in the first simulation round.

From the results in round 1, one can deduce that some locations need a supplementary source of biomass to lower the need for reserve fuel. This may involve waterway- or railway-based transportation. Another problem that could arise is storage-area limits at demand sites. To mitigate this factor, feed-in terminals could be situated near the relevant demand locations.

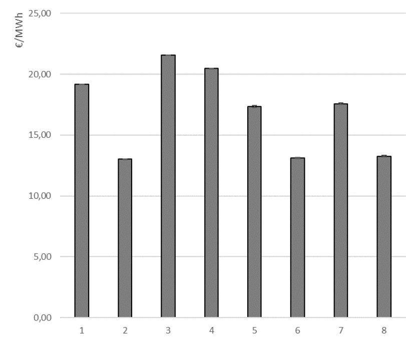
In the simulation work, there was assumed to be a feed-in terminal near the demand location, and the costs of transporting fuel from terminal to demand point were set to be 3.00 €/ton. Also, deliveries were transported by trucks with the capacity of 80 m^3 of loose material. As for thresholds for utilizing terminals, demand-point location's storage capacity was limited to 5,000 m^3 (loose).

Two scheduled supplementary deliveries were set up, to simulate modes of long-distance delivery such as trains or marine vessels. One arrived four times per month with 500 tons of uncomminuted biomass, and the other arrived five times during the peak usage season (October–March), bringing 1,000 tons of uncomminuted biomass each time. These deliveries were set to be the same for all demand locations, although some locations do not need them since the share of biomass used was high. The cost for these deliveries was set to be 50 EUR/ton.

With these modifications, demand locations with high reserve-fuel use ended up using more biomass and the acquisition costs fell (see Figure 3.10). At the same time, these costs rose for locations that had high biomass use in the first round. This is due to the supplementary deliveries incurring acquisition costs that were higher than that for local biomass though still lower than the costs for obtaining the reserve fuel. Use of terminals increased the costs too but did make it possible to have only 5,000 m^3 of loose storage at the demand location. The associated increase in costs would be higher if fixed costs (e.g., construction, servicing, and other costs for maintaining terminal operations) were included in the analysis.



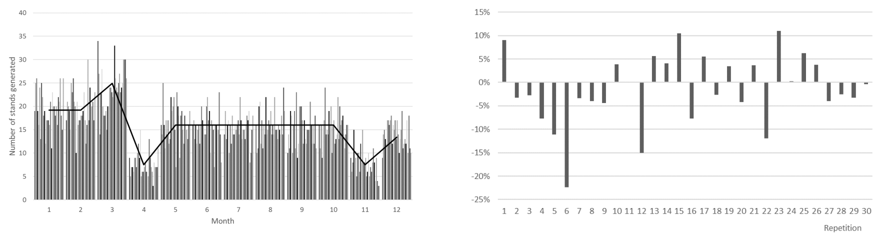
(a) Feedstock use



(b) Feedstock costs

Figure 3.10: The distribution of feedstock use and costs in the second simulation round.

For a local-scale study, the data have to be more precise than the input values for a region-level study. For this purpose, data may be preprocessed, as was done for Publication V to generate supply and moisture estimates as input to a multi-year simulation model. This enables one to consider annual supply variations while maintaining statistical validity (see Figure 3.11). Since the supply points are selected randomly and every supply point has a geographical location defined for it, the total transportation distance too varies annually.



(a) Number of harvesting-ready supply points

(b) Variation in feedstock availability

Figure 3.11: The number of harvesting-ready supply points each month, with the line showing the statistical value (a), and variations in the feedstock available over 30 generations.

Compared to Eriksson et al. (2017) method to generate random points inside the circle, the data processing method presented at Publication V takes into account local variables, such as limiting factors of the supply area (e.g. water bodies or urban areas) or harvesting times allocation due weather variables.

In addition to supply data, data for biomass quality were prepared. Using moisture-prediction models developed by Routa et al. (2015) and Heiskanen et al. (2014), it is possible to take account changes in quality. Moisture-prediction models use weather data such as precipitation and evaporation figures. Since measurements for evaporation cannot always be acquired, estimation connected with this was performed by means of Equation 2.5. This approach makes it possible to apply estimations without heavy use of initial data, but it decreases accuracy (see Figure 3.12). Although the evaporation estimation did generate negative values for wintertime, it is reasonable to use 0 in place of these values, since at low temperatures evaporation can be assumed to be negligible.

By using evaporation rates from Equation 2.5, one can estimate day-to-day changes in moisture content. Depending on the estimation approach used, various values can be obtained for estimation. Routa et al. (2015)'s estimation equation uses a coefficient and constant, and Heiskanen et al. (2014)'s approach requires factors a, b, and c. These values are determined by the type of biomass, storage, and other factors, and one must obtain them by means of either measurements or the literature. Oftentimes, using only estimations for factors in the model is acceptable as case specific values are hard to come by. However, the choice of estimation influences their effectiveness and effects model accuracy. During selection of the estimations, it is good to keep in mind that storages at simulation model are representations and every storage has its characteristics. Other factors too affect estimations, and it can be seen that, for instance, Heiskanen et al. (2014)'s approach is more suitable for estimates related to long-term storage than Routa et al. (2015)'s that may end up negative values with longer storing times (as Figure 3.13 indicates).

Figure 3.12: Estimated evaporation (Linacre, 1977; Heiskanen et al., 2014) and measured (SYKE, 2011) evaporation.

Routa et al. (2015) estimation model does show more daily variation that have higher importance in short storing times. As these estimations are made for theoretical storages, real moisture data cannot be used in comparison and there for fits to reality cannot be determine. Although, Raitila et al. (2015) compared both moisture content estimations with measured validation results from three validation storages and founded both estimation methods rendering good results with variation 0.4 to 3.2 %-unit for Routa et al. (2015) estimation and 0.2 to 2.8 %-unit for Heiskanen et al. (2014) estimation.

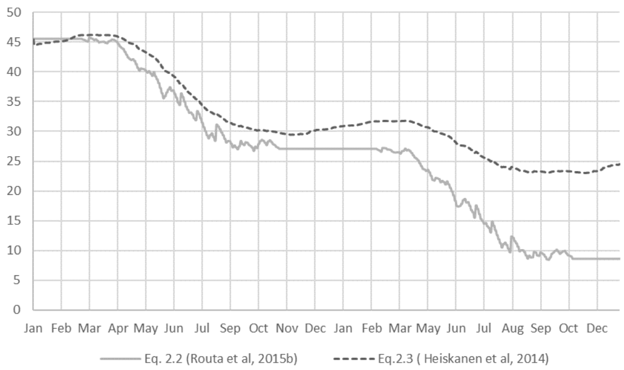


Figure 3.13: Estimates of moisture content, using 2011 weather data from the Mikkeli weather station and starting moisture of 45%. (Eq. 2.2: Coef=0.062, Const= 0.036; Eq. 2.3: a=0.0008, b=5, c=0.002)

The quantity of data needed for the simulation model depends on its level of abstraction. For Publications IV and V, the datasets for supply were similar in size, and in both studies the source of the data was a static biomass database. In a local-scale study, however, the data have to be preprocessed more, for the input data to be precise enough to support local variations. It is advisable to use actual measurements or enterprise data if possible, but this may be impossible in some cases. In that event, the data have to be estimated and preprocessed, to offer the best representation of the real-world situation.

4 Discussion

4.1 Increasing interest and awareness for ABM

Publication I conducted a bibliometric analysis of three computational modeling methods and of how these have been combined. It was found that interest in modeling methods has indeed increased and can be expected to continue growing. Awareness of simulation-based study methods and interest in them have been low, and a need to increase them has been identified in the simulation community (Siebers et al., 2010). Raising awareness of the potential use of ABM in teaching is of great importance since this should enable users to grow in number and encourage well-publicized cases of ABM's use.

Siebers et al. (2010) conducted panel discussion where they noted that ABM lacks tool-centered training material analogous to the textbook on Arena (DES software) produced by Kelton David et al. (2003). Manuals and other books have come out for training in modeling with ABM (Borshchev, 2013; Komosinski, 2005), thereby rendering learning to use the simulation tools easier. This is a step in the right direction, but, as was noted in the aforementioned panel discussion (Siebers et al., 2010), there are also problems of not having clear validation rules. As discussed in Publication I, reporting on ABM is complicated and guidelines would make it easier while also assisting in bringing about greater transparency of the work done.

Publication I shows that ABM has attracted at least some researchers, since it was considered the most novel method of the three methods considered in the publication. Furthermore, since the search was performed over titles, abstracts, and keywords, there is a high possibility that results representing multiple combinations of GIS and DTS were overlooked (since, for instance, using route networks is often not mentioned in abstracts). The GIS and LCA methods have the benefit of being static analysis methods. This entails both not needing as much computing power compared to dynamic simulations and having clear mathematical formulations at their base. In contrast, the dynamic element means that not all events can be explained readily via mathematical formulae, which renders the reporting of model and analyses of results challenging.

4.2 ABM as a research tool

ABM is a flexible tool that has multiple uses, as Publications I–V attest. Publication III shows how ABM can be used to study supply systems at the operator level, Publication II considers the geographical perspective, and Publication IV addresses the spatial element extended to European level. As Publication V illustrates, ABM can handle diverse types of data and process them as needed. Indeed, ABM has already been used for many studies, in numerous fields. Considering the biomass supply system operators as agents, makes it possible to study all elements of the supply system and how that system adapts to changes. This all can be done for an existing system or for a system that is under planning. In the case considered in Publication II, a supply system for pulpwood already existed, and it was modeled for comparison purposes. Other cases were modeled on the basis of a planned system that was expected to achieve savings on account of the relevant new policy allowing higher-capacity trucks to be part of the system.

Väätäinen et al. (2018) discussed simulations with regard to the many ways in which they can handle data, in different forms, such as results from formulae or variables. There are technical challenges in the use of Big Data – e.g., mathematical optimization, memory use, and software adaptivity (Reed and Dongarra, 2015). Challenges have been identified also in the use of light detection and ranging (LiDAR) for remote sensing in large-area studies, arising from the large quantity of data (Singh et al., 2016), and for Publication IV we were limited to loading data only from the study country so as to keep the magnitude of the data processable. Reed and Dongarra (2015) concluded that high-quality data and high-end computing are important for future research. At present, using Big Data for ABM leads to assumptions and generalization of data. Experiment-based measurements and enterprise data are more accurate but harder to come by. The work for Publication V preprocessed the data to eliminate the need for more specific data, but this resulted in the model's accuracy being lower. Publication III did use stochastic arrivals for trucks, since the study was done for a planning-phase plant. Väätäinen et al. (2005) used enterprise data to improve the material for an existing system, and this is recommendable if said data are available. For Publication IV, in turn, database material was used for the availability and roadside costs of biomass, while other values were taken from the literature. Since the study was a demonstration of the possibility of using a Big Data dataset in ABM, values were taken from Finnish measurements. The validity of the initial values was fairly low, but the model and logic were valid. Hence, the capabilities of the model even when using invalid values were proven.

Publications II and III examine the effect of new policy. In both cases, cost or time savings could be obtained by introducing HCT vehicles to the system, since fuller loading of trucks improves the efficiency of transportation. It is worth noting that Publication II does not take into account the costs associated with road maintenance and Publication III assumes that the plant yard is suitable for HCT vehicles, in terms of load-bearing capacity etc. These examples illustrate how a single policy change affects multiple point in the supply system, changing the dynamic behavior of the system. In awareness of this, Publication II presents logic customized specifically for HCT, leading to a more complicated logistics system for supply. The results described in Publication III, in turn, shows that HCT enables a smaller number of truck arrivals, thereby reducing the waiting times, but this would also cascade to a lower number of trucks driving in the area.

4.2.1 Data handling and incorporating other methods

ABM have good data handling properties, but it is important to understand how the used source data were compiled, since there are many methods of calculating availability, productivity, and other values that a database may offer. The work of Datta et al. (2017) presents multiple availability levels, with distinct names. Using details for the wrong sort of availability would lead to the wrong conclusion – for instance, as Publication IV notes, the costs not including the contract costs that usually would be covered in figures for roadside costs. To guarantee validity of the data and appropriate understanding of which data have been used, and how, transparency of the input data is important.

Publications II, IV, and V relied on GIS analysis for initial data. A powerful tool for handling geographical data, GIS sources represent good optimization potential. When used in combination with ABM, GIS enables having a spatial distribution of agents, including the route network in the model, distributing biomass availability spatially, and considering various other options. For Publication II, two road networks were included in the model, and the available feedstock was distributed in light of GIS data. Also, the HCT terminals and demand points' locations were set in line with the coordinate system. Publication IV presents the use of GIS analysis to address the availability of feedstock near particular demand points that are set in accordance with coordinates supplied by the user. Publication V shows how data from GIS analysis may be used to generate more precise values informing multi-year simulation for a plant producing energy from biomass. The use of GIS enables researchers to take spatial variation into consideration, just as ABM takes into account temporal variation.

4.2.2 Level of details

As ABM models are constructed started from individual agents, level of details are set at start of the creating of the model and selecting needed interactions and parameters. Since agents can have their own parameters, it is possible for interactions to be influenced by properties of all agents engaged in the interaction. For example, chipper productivity indicates how quickly a truck may be loaded and truck capacity dictates how much biomass may be loaded. Also, biomass type and moisture content may affect chipper productivity. For Publication III, the unloading times used for the trucks were based on the type of truck, truck capacity, and unloading rate, where the last of these was determined by the properties of the unloading area. Since unloading was an key part of the system, it was important to model this with low abstraction.

In contrast, for Publication II, it was assumed that forest trucks would unload their cargo onto the ground and HCT trucks would pick it up accordingly. This interaction, which is not as important for the system, was modeled with high abstraction. If the assumption had been different (e.g., assuming a regular truck unloading directly to an HCT truck), abstracting less in modeling of the interaction would have been important. The level of abstraction for interactions needs to be selected case-specifically. In this, the idea is not to get the interaction to mimic the real-world interaction as closely as possible but, rather, to get the modeled interaction to resulting same way as the real-world interaction in the manner best suiting the aim of the model.

Just as the abstraction level for interactions is case-specific, so is the level of abstraction for the model itself. Applying less abstraction in model usually tends to make the model more complicated. Since complexity of the model is not the goal, the abstraction level has to match the study area/case considered. In the work described in Publication IV, the supply of biomass was scaled to the grid of supply points, and we did not use the method of determining supply points annually that is presented in Publication V. This level of abstraction allowed us to conduct studies for multiple demand points and compare them with each other at European scale. In contrast, focusing on more local scale (smaller regions) and longer spans of time should drive the use more details.

4.2.3 Advantages and disadvantages of ABM

A simulation-based study method is similar to a digital prototype in how it is constructed digitally and used for testing. This is good to keep in mind throughout the development and use of the model: the prototype is not the final version, and it has limitations. The model may be developed to find something that cannot be found with other study methods, and its user can test how the system changes by altering various interactions. With the scenario-focused study method described here, one looks more at values that lead to a more beneficial state of the system, whereas a more traditional method would involve using data to improve the system and then, on the basis of the results, determining how much improvement actually resulted. When ABM is behind an academic paper, often the author has generated more scenarios than reported upon, and the best options were chosen for further consideration from among all of those generated. This leads to skewed reporting in that the work presents fewer scenarios and only the better ones, since there is no point in reporting on the worst scenarios. In Publication II, total of 82 scenarios were done by simulation and only 38 scenarios were qualified. Possibility to limit all scenarios involving 5200 t total truck capacity was an option, but to show the importance of the total truck capacity these were reported in the paper.

For some studies, simulation may enable considerable time savings, since a span of many years can be considered in just seconds. With Publications II and IV, the studies were done on the scale of months while the simulation unit was a year. Further emphasizing the time savings, these studies included multiple, quite different scenarios, each of which would have required a year-long experimental study. One downside to simulation is that it cannot incorporate perfectly detailed logic, leading to greater abstraction and a "big picture" view of the system. The simulation may account for small details via a probability distribution or other abstractions, but it cannot get as realistic as a demonstration study can. With regard to contracts, though, simulation offers a study method that does not affect real-world operations as the latter might, and it is easy to change case configurations in a simulation setting, as was done for Publication III. Also, as noted above, simulation enables carrying out studies with not-yet-existing systems, as was done in the work described in Publication IV.

With ABM, one can study interactions in the supply system in a manner that includes properties for all participants. These interactions are an important part of the supply system, since a bottleneck in one action cascades further in the system. In the ABM framework, the interactions are usually between two agents that exchange information with each other; one example is a delay of a roadside chipper leading to a chip-truck delay. This unique property of ABM allows more individual decision making than other simulation methods. Human behavior based on available information is possible to simulate with ABM, a behavior that has not been successfully simulated with DES (Siebers et al., 2010). However, Knight et al. (2012) did develop DES model that included agent-based decision making. There are multiple cases where DES can be used for studies even though ABM seems the best solution, and the other way around (Brailsford, 2014). Siebers et al. (2010) panel discussion and Brailsford (2014) response shows how DES and ADM may be used for similar problems. Choice of used methods is often based on personal preference and available tools. As Brailsford (2014) concludes, "Whether DES or ABS is better suited for these sorts of problem remains a mood point."

As a model's abstraction is reduced, the computing burden becomes heavier. This leads to limits in how detailed a model may be developed for a large-scale study. For instance, if the work presented in Publication II were to be expanded to nationwide scale, the computation requirements would rise, necessitating greater abstraction. In addition, other variables affect this balance. Computers' calculation power is rising, and, more importantly, modeling software is being refined further, opening the doors to creating more complicated models without using as much computing power. Although only a couple of year elapsed between the publications in the dissertation project, the modeling software was updated multiple times in the meantime, and performance has gotten better. Also, online simulation tools have been made available that allow the use of an off-site server for simulations and let one share simulation models with others easily.

During the development of the model, ABM focuses on building up from individual actions to the fully operative system (Macal and North, 2005). This allows developer focusing on logic of the individual and integrate it to the system. For modeler this allows focusing in one part of the system at a time, and does not require keeping in mind complete understanding of the entire system all the time. Building up from individual agents allows also to having unique properties for same type of agents and having this affect the system. Different capacity of trucks may have to select their driving route based on route limitations or biomass needs to be delivered to different locations, based on their quality. Individual decision making of the agents allow adapting human behavior in the model. Publications in this thesis do not use this advantage. Incorporating these to the model is challenging but for future development of studying biomass supply systems with ABM these should be taken into account.

4.3 Validation and credibility

Validation, referring to the model being sufficiently accurate for the purpose at hand (Carson, 1986), is often required for the simulation model. This is important sometimes, as it was for Publications II and III, when the results' accuracy affects the credibility of the model. On the other hand, it can be less vital. For Publication IV, validity was less important, because the study was designed for presenting a method of using Big Data with ABM and comparing the results at a high level of abstraction, although the credibility of the model was still important. The difference between credibility and validity can be characterized as involving a shift in perspective from the modeler's to the client's. For a model to possess credibility, the client has to believe the model is sufficiently accurate (Robinson, 2008). While a model may have been tested against the real world and determined to be valid (Robinson, 1999) by an accepted method, that may not make the model credible for the client. For the model to achieve credibility, it needs to be more transparently presented, so that the client understands how the solutions are produced. Client involvement in designing and modeling offers way to make model more credible and this practice is recommended.

The model's validity is important when one is studying policy or possible efficiency improvements to the system, since accuracy of the results is important for the decisions. Relatively academically oriented studies, in which the concern lies more with showing how given methods affect the system in general, do not need as much validity – the model has to be credible but need not always be accurate. Having lower validity allow the use of lower quality data and focusing on developing the method. Publishing developed method may be challenging due to publisher demanding validation of the model. This is understandable, as the journal wants high-quality papers, but as the developed method will be used by others, possible validation problems will come present and corrected leading the field of modeling development. Publication IV developed a method to use large dataset for European region study. Due limitations of the initial values, the results are not valid. However, the method and logic of the model are working as intended and results did have corresponding changes for different input values. It is reasonable to assume that with proper initial values the model would generate valid result sets, but giving limitations of initial values this cannot be shown in the paper. The purpose of the model determines the necessary level of validity and amount of credibility to the client.

Robinson (2008) notes that a 100% accurate model cannot be made and discusses the level of complexity needed for a valid model (see Figure 4.1). The reader is reminded that an overly complex model does not provide great gains in accuracy, and excessive detail may lead to a decline in accuracy (Robinson, 2008). An appropriate level of detail for the model is important. With too little detail, one may end up needing more assumptions and limiting the model's utility (Davies et al., 2003; Pritsker, 1986), while complexity is another factor. The work for Publication III used dynamic layout for the plant yard, and this made the model more complex than using a static layout. Using dynamic layout enables use of the model for various yard configurations, though, and study is not limited to only one size of yard. The model for Publication II was first used to study an existing system with quite a simple setup: transport wood from the forest to the plant with the given schedule and availability. The model's complexity did increase when HCT was introduced to the system: the model needed to determine whether HCT should be used and which terminal should be used. There is a "happy medium": the model should not be constructed to be simple purely for simplicity's sake, but over-complexity too should be avoided. As biomass supply systems develop further and as new policies' introduction and new machinery make the systems more complex, modelers need to take this balance into account, so that they develop useful models but, at the same time, address the more challenging validation and reporting involved.

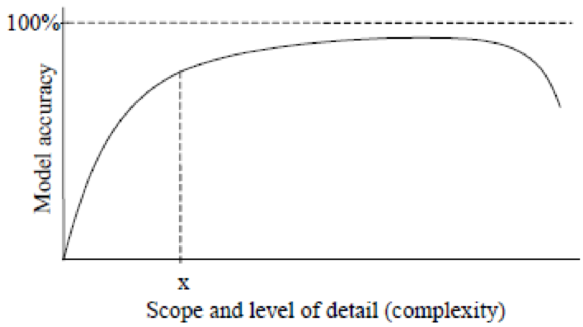


Figure 4.1: Simulation model complexity and accuracy (Robinson, 2008).

Simulation is often used in operations research and for industrial applications. This renders accuracy of the results important – the subject under study is a real system that the client wants to improve. Again, in much academic research, on the other hand, the results' accuracy is less important, since the model may be used to showcase a method or to highlight a mechanism in the system that is otherwise hard to demonstrate. In this kind of modeling, it is more important to have a credible model, showing that the model works as intended and that the results are comparable within the system represented. Validation of the model is one way to make a model credible, but performing validation may be rendered challenging by complexity of the model or by lack of data for comparison of results.

4.4 The issue of complex scenarios and results

Beside entailing complexity of the model, simulation-based studies generate large and complex result sets. This is visible with Publication II: 82 scenarios were generated, and there were eight replications for every scenario. The result set included costs, transportation distances, routes, and other information. Even though not all was reported, since some scenarios were disqualified, this is a large amount of material. For Publications III and IV, there were smaller result sets, since the studies' boundaries were more restricted. Sanchez and Lucas (2002) have discussed this problem, noting that the statistical design of experiments (DOE) may be beneficial for simulation studies. For experimental studies, DOE is used to limit the number of parameters, or factors, in the experiment. While simulation studies are cost-efficient and may produce multiple scenarios with little work, a model with 100 Boolean factors still involves 2^{100} (10^{30}) possible combinations, which is too many even for a simulation-based study. Additionally, there may be non-Boolean factors in the simulation model: numeric items or multi-option decisions. One approach is presented in Publication V; preprocessing data for the model, with generation of random initial parameters for a supply network that entails numerous combinations.

To overcome this problem, fewer runs may be carried out, with a lower-resolution design such as a grid layout or a random set of factors (Sanchez and Lucas, 2002), as seen with Publication V, for which we selected annual supply points at random from the list. Changing the seed for the random number generator produced a different set of supply locations as a random set of factors. When one is selecting scenarios, it is important to have a good design, so as to capture potential chaotic behavior or unexpected interactions. With Publication II, sensitivity analysis revealed a cost increase connected with increasing the proportion of HCT vehicles in the fleet. It can be assumed that as HCT utilization drops, on the other hand, and regular trucks' utilization increases, the lower number of standard trucks would not be able to satisfy the terminals and the HCT system hence would not yield the greatest possible benefit.

The stability of the experiment variance was not studied in the Publication II-IV as the models have high computational demands and multiple variables that would need to be studied, leading to impractical number of runs. Lorscheid et al. (2012) note that experimental variance needs to be interpreted with respect of the model and the number of runs needed to achieve stable results may not be affordable. Publications II-IV make repeatable runs to see how values change between runs with same initial values. Although this is better than using only one result set for reporting, it is worth noting that statistical analysis to find stable coefficient of variance was not conducted. Due to this reason, it cannot be exactly stated how stable the results are only how big variance there was between runs. As randomness has great part in the simulation studies and it generates experimental variance, or so called noise, true accuracy of the model cannot be found without knowing the level of noise.

4.5 Future work

It must be reiterated that, since computational modeling method are relatively new, the terminology is still evolving, and the use of keywords varies between authors accordingly. The problem is even greater for reporting related to the models, and the terms used differ with the author. This hinders sharing of models and of knowledge more generally. This problem arises even in sharing of models inclusive of source code. The scientific literature databases examined for Publication I mitigate this problem by generating keywords automatically. This makes publications easier to find but does sometimes lead to inappropriate keywords. The system is good but needs to be developed further. The matters highlights the importance of the author using good, descriptive keywords.

The model's transparency in the reporting makes it more credible. Because validation of the model may be problematic, it is important to increase transparency and credibility. The ABM approach tends to generate complex models, which makes reporting on them challenging. Simple models are easier to report upon, but they may not be sufficient for representing a complex system. Grimm et al. (2006) developed ODD (Overview, Design concepts, and Details) protocol for reporting on ABM and issued a revised version in 2010 (Grimm et al., 2010). Revised version of ODD was used in Publication II and III, but Publication IV was reported without standard. This was due limited length of paper that ODD would have exceeded. As ODD needs to be self explanatory it often leads repetition as system descriptions have to be explained in context of the study and in the context of the model. Use of ODD or other standard is usually recommended but in some cases the model is simple enough to be described without standard. Standardized reporting for a simple model may be justified by having a common reporting format. Improving the reporting and standardizing it should help to improve the models' transparency and sharing of information. Having a standard reporting method also makes teaching of the reporting more uniform and increases the commonality of practice, giving new modelers more easily understandable literature to study. To raise awareness of efforts to standardize the reporting and to increase interest in it, one should apply standards and explicitly cite the standards followed.

Modeling may focus in specific action in the supply system, but larger models take into multiple actions account. This leads the model to include several different logics to represent actions and need to explain every logic with high details. Publication V presents a method to allocate supply for the simulation model, enabling the possibility to refer to this paper in future models using the same method. This allows the report to focus on reporting results. The downside is breaking reporting to multiple different sources, leading discontinuity of the report. Some methods, that may be used for biomass supply system simulation models, have been published (e.g. moisture forecast (Sikanen et al., 2013; Routa et al., 2015), forest production chain (Ziesak et al., 2004)) and more should be developed in the future to allow incorporating different methods to larger models with ease.

In this thesis, GIS was used with two models, and data preprocessing was applied to data generated from GIS analysis. This approach provides spatial information to the dynamic model. This relationship allows the simulation study of spatial and temporal variation. Because of the carbon-neutral nature of biomass itself, studies often neglect associated emissions. Since other activities in the supply system produce emissions, it would be beneficial to incorporate LCA into studies involving biomass. Indeed, work combining LCA with ABM was found in the bibliometric analysis presented in Publication I (Davis et al., 2009; Bichraoui-Draper et al., 2015). Reviews have noted ABM's dynamic nature lending dynamic aspects to study of this type. Also, the implications for uncertainty analysis were found to be important. Since these and other advantages of combining ABM with LCA are clear, further work on frameworks and on methods for this should be done. In addition, including GIS in the combination allows research into biomass-related emissions to encompass both spatial and temporal aspects. These aspects are important in studies of land-use changes, biomass transportation, energy production, conversion systems, and other activities including biomass.

Since ABM is considered a novel study method, generating awareness of it and increasing interest in ABM is important. This would enable more instances of application of ABM and encourage software development, thereby contributing to better modeling tools. One important part of generating awareness is training in ABM and in use of the relevant software. The rarity of academic training in modeling and simulation impose limits to new researchers' use of ABM as a tool, and complexities in software discourage independent learning. That said, software developers have been publishing more software-centered literature lately, with Borshchev (2013) and Railsback and Grimm (2011) being examples, and tutorials are available for most software, lowering the threshold to learning its use.

5 Conclusions

As the publications show, ABM is a flexible tool with many applications. Publication I verifies an increase in interest in applying modeling methods in biomass supply system studies, ABM among them. Still discussion of validation and credibility of ABM models is needed, to guarantee appropriate use of the models and creation of a foundation to consolidate reporting for industry and academic use of ABM. This encourages greater awareness of simulation studies but also provides room for different ways to publish results.

Publications II–IV present biomass supply systems' examination with ABM and simulation of several distinct scenarios. All of the studies involved systems that were not yet implemented, with Publication II taking an existing system as a base scenario. Agent-based modeling gives the possibility of simulating possible future scenarios and comparing the results, thereby yielding insight into potential reactions to actions taken today. For this to be as valuable as possible, multiple scenarios, with different initial values, need to be run. The problem of the multitude of combinations of initial factors can be reduced by using DOE methodology to select suitable initial values. Scenario selection is an important phase of simulation-based study, because the number of scenarios is limited by time and computation power yet enough scenarios still have to be included to capture the chaotic behavior of the system.

A biomass supply system encompasses multiple operations and interactions that are amenable to study with ABM. Publication V shows how ABM may be initialized for spatially and temporally scattered supply. Publication III demonstrates how activities at operator level may be examined by means of simulation studies, and Publication II and Publication IV examine how the supply system, from origin source to demand point, may be studied at different geographical levels. The ABM approach's good data-handling, cost-efficiency, flexibility, and rapid scenario analysis prove this method to be well suited to utilization as a biomass supply system research tool as it offers multiple advantages compared to the traditional study methods.

Biomass supply systems involve many interactions and elements of information exchange that can be modeled with ABM. As systems become more complicated, the models too tend to get more complex, and this complicates their creation, use, and reporting. Consistent and coherent reporting on ABM studies is necessary to enable more appropriate sharing of information and a more solid base for joint projects and studies.

The good data-handling of ABM enables the possibility of combining GIS and ABM to include spatial variation in a dynamic simulation study. Since GIS can be directed to many purposes, it may be used in many ways to accompany ABM. For Publications II and IV, road-network and feedstock-availability data were used to make transportation distances and spatially accurate input available in the model. There is also the possibility of including LCA, to integrate environment and emission analyses, and this has indeed been done in a few studies, pointed out in Publication I. Although challenging, adding a temporal aspect to the LCA would be beneficial for future studies.

Introducing new policies and machinery to a biomass supply system affects the system, and studying these effects is not always viable or possible at all with traditional study methods. Supply systems' complex nature is well suited to being studied with ABM, and more information about system changes can be gained from a comprehensive study of scenarios.

The publications of this thesis show that using ABM as part of the set of tools for study of biomass supply systems enables:

- Studies at different geographical and operation scales, with the possibility of studying both existing and not-yet-existing systems without disturbing the existing system.
- Inclusion of a large quantity of data and application of good data-handling capabilities.
- Use of GIS data for estimating biomass availability and for including the road network for obtaining realistic transport distances.
- Generation of multiple scenarios, for studying multiple effects in the system cost-efficiently.

The discussion here has identified the following challenges and development opportunities for ABM:

- Since ABM is a novel study method, the terminology and methods are still developing.
- Validation and reporting results are less than standardized and are somewhat cumbersome.
- The modeling software is complicated and not attractive to new users.
- Interest and awareness are rising, but further work remains for the future.

References

Abdou, M., Hamill, L., and Gilbert, N. (2012). Designing and building an agent-based model. In: *Agent-based models of geographical systems*, pp. 141–165. Springer.

Alakangas, E., Routa, J., Asikainen, A., and Nordfjell, T., eds, (2015). *Innovative, effective and sustainable technology and logistics for forest residual biomass: Summary of the INFRES project results*, INFRES Reports.

Allan, R.J. (2010). *Survey of agent based modelling and simulation tools*. Science & Technology Facilities Council.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., et al. (1998). Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. *Fao, Rome*, 300(9), p. D05109.

An, H., Wilhelm, W.E., and Searcy, S.W. (2011). Biofuel and petroleum-based fuel supply chain research: A literature review. *Biomass and Bioenergy*, 35(9), pp. 3763 – 3774. ISSN 0961-9534, doi:10.1016/j.biombioe.2011.06.021.

Bandini, S., Manzoni, S., and Vizzari, G. (2009). Agent based modeling and simulation: An informatics perspective. *JASSS*, 12(4).

Becker, M., Wenning, B.L., Görg, C., Gehrke, J.D., Lorenz, M., and Herzog, O. (2006). Agent-based and discrete event simulation of autonomous logistic processes. *Proceedings of: Borutzky, W.; Orsoni, A.; Zobel, R.(eds.)*, pp. 566–571.

Bichraoui-Draper, N., Xu, M., Miller, S.A., and Guillaume, B. (2015). Agent-based life cycle assessment for switchgrass-based bioenergy systems. *Resources, Conservation and Recycling*, 103, pp. 171–178.

Borshchev, A. (2013). *The Big Book of Simulation Modeling: Multimethod Modeling with Anylogic 6*. AnyLogic North America. ISBN 0989573176.

Borshchev, A. and Filippov, A. (2004). From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools.

Brailsford, S. (2014). Discrete-event simulation is alive and kicking! *Journal of Simulation*, 8(1), pp. 1–8. doi:10.1057/jos.2013.13.

Carson, J.S. (1986). Simulation Series. 2. Convincing Users of Models Validity is Challenging Aspect of Modelers Job. *Industrial Engineering*, 18(6), p. 74.

Chaplin-Kramer, R., Sim, S., Hamel, P., Bryant, B., Noe, R., Mueller, C., Rigarlsford, G., Kulak, M., Kowal, V., Sharp, R., et al. (2017). Life cycle assessment needs predictive spatial modelling for biodiversity and ecosystem services. *Nature communications*, 8, p. 15065.

Datta, P., Dees, M., Elbersen, A.F.B., Staritsky, I., and DLO-Alterra (2017). *D1.5 The data base of biomass cost supply data for EU28, Western Balkan Countries, Moldova, Turkey and Ukraine*. Chair of Remote Sensing and Landscape Information Systems, Institute of Forest Sciences, University of Freiburg, Germany.

Davies, R., Roderick, P., and Raftery, J. (2003). The evaluation of disease prevention and treatment using simulation models. *European Journal of Operational Research*, 150(1), pp. 53–66.

Davis, C., Nikolić, I., and Dijkema, G.P. (2009). Integration of life cycle assessment into agent-based modeling: Toward informed decisions on evolving infrastructure systems. *Journal of Industrial Ecology*, 13(2), pp. 306–325.

Delval, F., Guo, M., van Dam, K., Stray, J., Haigh, K., Görgens, J., and Shah, N. (2016). Integrated multi-level bioenergy supply chain modelling applied to sugarcane biorefineries in South Africa. *Computer Aided Chemical Engineering*, 38, pp. 2037–2042. doi:10.1016/B978-0-444-63428-3.50344-1.

Demirbas, M., Balat, M., and Balat, H. (2009). Potential contribution of biomass to the sustainable energy development. *Energy Conversion and Management*, 50(7), pp. 1746–1760. doi:10.1016/j.enconman.2009.03.013.

Eliasson, L., Eriksson, A., and Mohtashami, S. (2017). Analysis of factors affecting productivity and costs for a high-performance chip supply system. *Applied Energy*, 185, pp. 497–505. ISSN 0306-2619, doi:10.1016/J.APENERGY.2016.10.136.

Erber, G., Kanzian, C., Stampfer, K., et al. (2012). Predicting moisture content in a pine logwood pile for energy purposes. *Silva Fennica*, 46(4), pp. 555–567.

Eriksson, A., Eliasson, L., Sikanen, L., Hansson, P.A., and Jirjis, R. (2017). Evaluation of delivery strategies for forest fuels applying a model for Weather-driven Analysis of Forest Fuel Systems (WAFFS). *Applied energy*, 188, pp. 420–430. doi:10.1016/j.apenergy.2016.12.018.

Field, C., Campbell, J., and Lobell, D. (2008). Biomass energy: the scale of the potential resource. *Trends in Ecology and Evolution*, 23(2), pp. 65–72. doi:10.1016/j.tree.2007.12.001.

Finkbeiner, M., Inaba, A., Tan, R., Christiansen, K., and Klüppel, H.J. (2006). The new international standards for life cycle assessment: ISO 14040 and ISO 14044. *The international journal of life cycle assessment*, 11(2), pp. 80–85.

FMI (2011). *Weather and sea, Download observations*. url: `https://en.ilmatieteenlaitos.fi/download-observations/`. Finnish Meteorological Institute. Accessed 16.10.2018.

Gallego-Elvira, B., Baille, A., Martín-Gorriz, B., Maestre-Valero, J., and Martínez-Alvarez, V. (2012). Evaluation of evaporation estimation methods for a covered reservoir in a semi-arid climate (south-eastern Spain). *Journal of Hydrology*, 458-459, pp. 59 – 67. ISSN 0022-1694, doi:10.1016/j.jhydrol.2012.06.035.

Goldemberg, J. and Coelho, S.T. (2004). Renewable energy?traditional biomass vs. modern biomass. *Energy Policy*, 32(6), pp. 711 – 714. ISSN 0301-4215, doi:10.1016/S0301-4215(02)00340-3.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., et al. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological modelling*, 198(1-2), pp. 115–126.

Grimm, V., Berger, U., DeAngelis, D.L., Polhill, J.G., Giske, J., and Railsback, S.F. (2010). The ODD protocol: a review and first update. *Ecological modelling*, 221(23), pp. 2760–2768.

Heiskanen, V.P., Raitila, J., and Hillebrand, K. (2014). *Varastokasassa olevan energiapuun kosteuden muutoksen mallintaminen [modeling of moisture change in energy wood in a storage]*. VTT Technical Research Centre of Finland. Report VTT-R-08637-13.

Jäppinen, E., Korpinen, O.J., Laitila, J., and Ranta, T. (2014). Greenhouse gas emissions of forest bioenergy supply and utilization in Finland. *Renewable and Sustainable Energy Reviews*, 29, pp. 369–382. doi:10.1016/j.rser.2013.08.101.

Kanzian, C., Kühmaier, M., and Erber, G. (2016). Effects of moisture content on supply costs and CO2 emissions for an optimized energy wood supply network. *Croatian Journal of Forest Engineering: Journal for Theory and Application of Forestry Engineering*, 37(1), pp. 51–60.

Kelton David, W., Sadowski Randall, P., and Sturrock David, T. (2003). *Simulation with arena*. New York: Mc Graw Hill.

Kishita, Y., Nakatsuka, N., and Akamatsu, F. (2017). Scenario analysis for sustainable woody biomass energy businesses: The case study of a Japanese rural community. *Journal of cleaner production*, 142, pp. 1471–1485.

Knight, V.A., Williams, J.E., and Reynolds, I. (2012). Modelling patient choice in healthcare systems: development and application of a discrete event simulation with agent-based decision making. *Journal of Simulation*, 6(2), pp. 92–102.

Komosinski, M. (2005). Framsticks: A platform for modeling, simulating, and evolving 3D creatures. In: *Artificial life models in software*, pp. 37–66. Springer.

Krishnan, B.R. (2016). *Biomass residues for power generation : A simulation study of their usage at Liberia ' s plantations*. Ph.D. thesis. University of Michigan.

Laitila, J., Prinz, R., Routa, J., Kokko, K., Kaksonen, P., Suutarinen, J., and Eliasson, L. (2015). Prototype of hybrid technology chipper-D4. 6.

Lee, Y.H., Cho, M.K., Kim, S.J., and Kim, Y.B. (2002). Supply chain simulation with discrete-continuous combined modeling. *Computers and Industrial Engineering*, 43(1-2), pp. 375–392. ISSN 03608352, doi:10.1016/S0360-8352(02)00080-3.

Leemis, L.M. and Park, S.K. (2006). *Discrete-Event Simulation: A First Course*. Pearson.

Liang, T., Khan, M., and Meng, Q. (1996). Spatial and temporal effects in drying biomass for energy. *Biomass and Bioenergy*, 10(5-6), pp. 353–360.

Linacre, E.T. (1977). A simple formula for estimating evaporation rates in various climates, using temperature data alone. *Agricultural Meteorology*, 18(6), pp. 409 – 424. ISSN 0002-1571, doi:10.1016/0002-1571(77)90007-3.

Lorscheid, I., Heine, B.O., and Meyer, M. (2012). Opening the 'Black Box' of Simulations: Increased Transparency and Effective Communication Through the Systematic Design of Experiments. *Computational and Mathematical Organization Theory*, 18(1), pp. 22–62. doi:10.1007/s10588-011-9097-3.

LUKE (2018a). *Biomass-atlas*. url: `https://www.luke.fi/biomassa-atlas/en/`. Natural Resources Institute Finland. Accessed 16.10.2018.

LUKE (2018b). *Industrial Roundwood Removals and Labour Force - Harvesting Volumes of Energy Wood Per Month*. url: `http://statdb.luke.fi/PXWeb/pxweb/en/LUKE/`. Natural Resources Institute Finland. Accessed 21.02.2019.

Luo, K., Zhang, X., and Tan, Q. (2016). Novel Role of Rural Official Organization in the Biomass-Based Power Supply Chain in China: A Combined Game Theory and Agent-Based Simulation Approach. *Sustainability*, 8(8), p. 814. doi:10.3390/su8080814.

Macal, C.M. and North, M.J. (2005). Tutorial on agent-based modeling and simulation. In: *Proceedings of the Winter Simulation Conference, 2005.*, pp. 14 pp.–. ISSN 0891-7736.

Macal, C.M. and North, M.J. (2010). Tutorial on agent-based modelling and simulation. *Journal of simulation*, 4(3), pp. 151–162.

Marques, A., Borges, J., Sousa, P., Fonseca, M., Gonçalves, J., and Oliveira, J. (2012). *An Enterprise Architecture Approach for designing an Integrated Wood Supply Management System*, pp. 1–22. IGI Global.

McCormick, K. and Kåberger, T. (2007). Key barriers for bioenergy in Europe: Economic conditions, know-how and institutional capacity, and supply chain co-ordination. *Biomass and Bioenergy*, 31(7), pp. 443 – 452. ISSN 0961-9534, doi:10.1016/j.biombioe.2007.01.008.

Mertens, A., Van Meensel, J., Willem, L., and Buysse, J. (2016). Can resource competition encourage market development? A case study on the development of a corn stover market in Flanders. pp. 1431–1440.

Mertens, A., Van Meensel, J., Willem, L., Lauwers, L., and Buysse, J. (2018). Ensuring continuous feedstock supply in agricultural residue value chains: A complex interplay of five influencing factors. *Biomass and Bioenergy*, 109, pp. 209–220. doi:10.1016/j.biombioe.2017.12.024.

Mirkouei, A., Haapala, K.R., Sessions, J., and Murthy, G.S. (2017). A mixed biomass-based energy supply chain for enhancing economic and environmental sustainability benefits: A multi-criteria decision making framework. *Applied energy*, 206, pp. 1088–1101.

Mobini, M., Sowlati, T., and Sokhansanj, S. (2011). Forest biomass supply logistics for a power plant using the discrete-event simulation approach. *Applied Energy*, 88(4), pp. 1241–1250.

Moncada, J., Lukszo, Z., Junginger, M., Faaij, A., and Weijnen, M. (2017a). A conceptual framework for the analysis of the effect of institutions on biofuel supply chains. *Applied Energy*, 185, pp. 895–915. doi:10.1016/j.apenergy.2016.10.070.

Moncada, J., Junginger, M., Lukszo, Z., Faaij, A., and Weijnen, M. (2017b). Exploring path dependence, policy interactions, and actor behavior in the German biodiesel supply chain. *Applied Energy*, 195, pp. 370–381. doi:10.1016/j.apenergy.2017.03.047.

Moncada, J.A., Junginger, M., Lukszo, Z., Faaij, A., and Weijnen, M. (2015). Agent-based model of the German Biodiesel Supply Chain. In: *Computer Aided Chemical Engineering*, vol. 37, pp. 2045–2050. Elsevier.

Monteith, J. (1981). Evaporation and surface temperature. *Quarterly Journal of the Royal Meteorological Society*, 107(451), pp. 1–27.

Pritsker, A.A.B. (1986). Model evolution: a rotary index table case history. In: *Proceedings of the 18th conference on Winter simulation*, pp. 703–707.

Ragwitz, M., Schade, W., Breitschopf, B., Walz, R., Helfrich, N., Rathmann, M., Resch, G., Panzer, C., Faber, T., Haas, R., et al. (2009). The impact of renewable energy policy on economic growth and employment in the European Union. *Brussels, Belgium: European Commission, DG Energy and Transport*.

Railsback, S.F. and Grimm, V. (2011). *Agent-based and individual-based modeling: a practical introduction*. Princeton university press.

Raitila, J., Heiskanen, V.P., Routa, J., Kolström, M., and Sikanen, L. (2015). Comparison of moisture prediction models for stacked fuelwood. *BioEnergy Research*, 8(4), pp. 1896–1905.

Ranta, T., Halonen, P., Frilander, P., Asikainen, A., Lehikoinen, M., and Väätäinen, K. (2002). Logistics of long-distance truck transportation of forest chips [Metsähakkeen autokuljetuksen logistiikka - PUUT20]. *VTT Symposium (Valtion Teknillinen Tutkimuskeskus)*, (221), pp. 119–133.

Reed, D.A. and Dongarra, J. (2015). Exascale computing and big data. *Communications of the ACM*, 58(7), pp. 56–68.

Rentizelas, A.A., Tolis, A.J., and Tatsiopoulos, I.P. (2009). Logistics issues of biomass: the storage problem and the multi-biomass supply chain. *Renewable and sustainable energy reviews*, 13(4), pp. 887–894. doi:10.1016/j.rser.2008.01.003.

Robinson, S. (1999). Simulation verification, validation and confidence: a tutorial. *Transactions of the Society for Computer Simulation*, 16(2), pp. 63–69.

Robinson, S. (2008). Conceptual modelling for simulation Part I: definition and requirements. *Journal of the operational research society*, 59(3), pp. 278–290.

Routa, J., Kolström, M., Ruotsalainen, J., and Sikanen, L. (2015). Validation of prediction models for estimating the moisture content of small diameter stem wood. *Croatian Journal of Forest Engineering: Journal for Theory and Application of Forestry Engineering*, 36(2), pp. 283–291.

Salama, M., Yousef, K., and Mostafa, A. (2015). Simple equation for estimating actual evapotranspiration using heat units for wheat in arid regions. *Journal of Radiation Research and Applied Sciences*, 8(3), pp. 418 – 427. ISSN 1687-8507, doi: 10.1016/j.jrras.2015.03.002.

Sanchez, S.M. and Lucas, T.W. (2002). Exploring the world of agent-based simulations: simple models, complex analyses: exploring the world of agent-based simulations: simple models, complex analyses. In: *Proceedings of the 34th conference on Winter simulation: exploring new frontiers*, pp. 116–126.

Sargent, R.G. (2009). Verification and validation of simulation models. In: *Simulation Conference (WSC), Proceedings of the 2009 Winter*, pp. 162–176.

Sayama, H. (2015). *Introduction to the modeling and analysis of complex systems*. Open SUNY Textbooks.

Schelling, T.C. (1971). Dynamic models of segregation. *Journal of mathematical sociology*, 1(2), pp. 143–186.

Schriber, T.J., Brunner, D.T., and Smith, J.S. (2014). Inside Discrete-event Simulation Software: How IT Works and Why It Matters. In: *Proceedings of the 2014 Winter Simulation Conference*, WSC '14, pp. 132–146. Piscataway, NJ, USA: IEEE Press.

Siebers, P.O., Macal, C.M., Garnett, J., Buxton, D., and Pidd, M. (2010). Discrete-event simulation is dead, long live agent-based simulation! *Journal of Simulation*, 4(3), pp. 204–210.

Sikanen, L., Röser, D., Anttila, P., and Prinz, R. (2012). Forecasting algorithm for natural drying of energy wood in forest storages. *Forest Energy Observer. Study Report*, 27.

Sikanen, L., Röser, D., Anttila, P., and Prinz, R. (2013). Forecasting Algorithm for Natural Drying of Energy Wood in Forest Storages. *Forest Energy Observer*, 27.

Sikanen, L., Korpinen, O.J., Tornberg, J., Saarentaus, T., Leppänen, K., and Jahkonen, M. (2016). *Energy Biomass Supply Chain Concepts Including Terminals*. ISBN 9789527205082.

Singh, A., Chu, Y., and You, F. (2014). Biorefinery supply chain network design under competitive feedstock markets: an agent-based simulation and optimization approach. *Industrial & Engineering Chemistry Research*, 53(39), pp. 15111–15126.

Singh, K.K., Chen, G., Vogler, J.B., and Meentemeyer, R.K. (2016). When big data are too much: Effects of LiDAR returns and point density on estimation of forest biomass. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9(7), pp. 3210–3218.

Surana, A., Kumara *, S., Greaves, M., and Raghavan, U.N. (2005). Supply-chain networks: a complex adaptive systems perspective. *International Journal of Production Research*, 43(20), pp. 4235–4265. ISSN 0020-7543, doi:10.1080/00207540500142274.

SYKE (2011). *Hydrologiset kuukausitilastot [Hydrological Monthly Statistics]*. url: `http://wwwi3.ymparisto.fi/i3/paasivu/fin/etusivu/etusivu.htm`. Natural Resources Institute Finland. Accessed 16.10.2018.

Väätäinen, K. et al. (2018). Developing forest chips supply chains by redesigning supply operations and logistics.

Varga, A. (2001). Discrete event simulation system. In: *Proc. of the European Simulation Multiconference (ESM'2001)*.

Venäläinen, P. and Korpilahti, A. (2015). HCT-ajoneuvoyhdistelmien vaikutus puutavarakuljetusten tehostamisessa–Esiselvitys.

Väätäinen, K., Asikainen, A., and Eronen, J. (2005). Improving the Logistics of Biofuel Reception at the Power Plant of Kuopio City. *International Journal of Forest Engineering*, 16(1), pp. 51–64. doi:10.1080/14942119.2005.10702507.

Wasajja, H. and Daniel Chowdhury, S. (2017). Evaluation of advanced biomass technologies for rural energy supply. pp. 1272–1276.

Windisch, J., Väätäinen, K., Anttila, P., Nivala, M., Laitila, J., Asikainen, A., and Sikanen, L. (2015). Discrete-event simulation of an information-based raw material allocation process for increasing the efficiency of an energy wood supply chain. *Applied Energy*, 149, pp. 315–325.

Xiang, X., Kennedy, R., Madey, G., and Cabaniss, S. (2005). Verification and validation of agent-based scientific simulation models. In: *Agent-directed simulation conference*, pp. 47–55.

Yazan, D., Fraccascia, L., Mes, M., and Zijm, H. (2018). Cooperation in manure-based biogas production networks: An agent-based modeling approach. *Applied Energy*, 212, pp. 820–833. doi:10.1016/j.apenergy.2017.12.074.

Zamora-Cristales, R., Boston, K., Sessions, J., and Murphy, G. (2014). Stochastic simulation and optimization of mobile chipping economics in processing and transport of forest biomass from residues. *Silva Fennica*, 47(5). ISSN 22424075, doi:10.14214/sf.937.

Zeigler, B.P., Kim, T.G., and Praehofer, H. (2000). *Theory of modeling and simulation*. Academic press.

Zhang, X., Luo, K., and Tan, Q. (2016). A feedstock supply model integrating the official organization for China's biomass generation plants. *Energy Policy*, 97, pp. 276–290. ISSN 03014215, doi:10.1016/j.enpol.2016.07.027.

Ziesak, M., Bruchner, A.K., and Hemm, M. (2004). Simulation technique for modelling the production chain in forestry. *European Journal of Forest Research*, 123(3), pp. 239–244. ISSN 1612-4677, doi:10.1007/s10342-004-0028-4.

Publication I

Aalto, M., Racghu, KC., Korpinen, O-J., Ranta. T.
Modeling of Biomass Supply System by Combining Computational Methods – A Review Article

Applied Energy
Vol. 243, pp. 145–154, 2019

Applied Energy 243 (2019) 145–154

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Modeling of biomass supply system by combining computational methods – A review article

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HIGHLIGHTS

- Publications using combination of modeling methods, LCA, GIS and DTS were reviewed.
- Rising number of publications for methods, indicate increase in interest.
- Future work towards uniform terminology and reporting were recommended.
- Possibility to use simpler models to support other models were recommended.
- Conclusion of models combination extending results gained in the study was done.

ARTICLE INFO

Keywords:
Biomass
Supply chain
Life cycle assessment
Geographical information system
Agent-based modeling and simulation
Discrete-event simulation

ABSTRACT

As computing power increases, more complex computational models are utilized for biomass supply system studies. The paper describes three commonly used modeling methods in this context, geographic information systems, life-cycle assessment, and discrete-time simulation and presents bibliometric analysis of work using these three study methods. Of the 498 publications identified in searches of the Scopus and Web of Science databases, 17 reported on combinations of methods: 10 on life-cycle assessment and geographic information systems, six on joint use of life-cycle assessment and discrete-time simulation, and one on use of geographic information systems jointly with discrete-time simulation. While no articles dealt directly with simultaneous use of all three methods, several acknowledged the potential of this. The authors discuss numerous challenges identified in the review that arise in combining methods, among them computational load, the increasing number of assumptions, guaranteeing coherence between the models used, and the large quantities of data required. Discussion of issues such as the complexity of reporting and the need for standard procedures and terms becomes more critical as repositories bring together research materials, including entire models, from various sources. Efforts to mitigate many of modeling's challenges have involved phase-specific modeling and use of such methods as expressions or uncertainty analysis in place of a complex secondary model. The authors conclude that combining modeling methods offer considerable potential for taking more variables into account; improving the results; and benefiting researchers, decision-makers, and operation managers by producing more reliable information.

1. Introduction

Continuing advances in computing power have made it possible to develop larger-scale and more complex computational models that may be utilized in biomass supply chain analyses. These models enable studies that expenses or practical constraints to operations might render impossible to conduct in the real world [1]. Thanks to greater computing power, multiple modeling methods can be applied in combination to study biomass supply systems. Which of the many available modeling methods are employed in a given case depends on the study subject, the tools at hand, and the researchers' expertise. To examine the landscape, bibliometric analysis was conducted to reveal the latest developments in modeling methods' usage. This involved a review of articles reporting on joint use of two or more modeling methods in biomass supply chain analysis.

Researcher interest in modeling as an approach to studying bioenergy systems is evident from the rising number of papers presenting reviews in this field [2–6]. The categorization of modeling methods, which are typically referred to as mathematical models in this domain, varies from one review to the next. These models, described as sets of

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https://doi.org/10.1016/j.apenergy.2019.03.201
Received 8 January 2019; Received in revised form 15 February 2019; Accepted 29 March 2019
Available online 03 April 2019

equations that characterize real-world phenomena [7], were divided into three classes by De Meyer et al. (2014) [2] and by Ghaderi et al. (2016) [6]: the mathematical programming, multi-criteria decision-making, and heuristic approaches. Meanwhile, Sharma et al. (2013) [4] considered four classes of mathematical model: deterministic, stochastic, hybrid, and IT-driven, where they clarified the last of these consists of models that use application software to coordinate and integrate phases in the supply chain on a real-time basis. Wang et al. (2015) [5], in turn, did not enumerate a typology of mathematical models, only distinguishing among models based on geographic information systems (GIS), life-cycle assessment (LCA), crop-growth models, joint use of process models and reaction kinetics, and mathematical models that have been developed specifically to analyze and optimize complex biomass supply systems. Finally, Awudu and Zhang (2012) [3] took a simpler approach by splitting models into only two classes: analytical methods and simulation methods.

In Awudu and Zhang's terms, analytical methods include linear programming, mixed integer linear programming, integer stochastic programming, and other methods that involve "mathematical programming." Mathematical programming optimizes the given system by minimizing or maximizing the values resulting from certain decisions in line with set constraints and objective functions [8]. Since these methods, which many scholars have concluded are popular [2–6], are employed for optimization purposes, they can be seen as a suitable for extended use involving other methods, such as GIS-based methods [2]. Since mathematical programming and combined uses involving it have been extensively reviewed already, these are excluded from consideration here. This paper focuses instead on three methods that are used particularly often in biomass supply system studies – the GIS, LCA, and discrete-time simulation (DTS) approaches, where the last of these encompasses such tools as discrete-event simulation (DES) and agent-based modeling and simulation (ABM). Together, these can cover the spatial, temporal, and environmental aspects of the system under study.

Biomass supply chains display spatial variation with regard to, for instance, the distribution of feedstock-generation locations, the location of the various operations, and long transport distances. Through GIS tools, researchers can assess the effects of these variables on the system. Environmental factors too are important, since, while biomass is generally considered carbon-neutral and its use is often promoted for environmental reasons, the reality may be more complicated. This can be addressed by LCA. Finally, DTS can cover temporal challenges in the system, such as hot-chain issues, supply-and-demand problems, and changes in feedstock availability. Each of the three approaches addresses particular important facets of the system. Since these overlap little, applying multiple methods can yield more comprehensive results, giving practitioners and academics more information and, thereby, greater opportunities to understand system mechanics and the consequences of change in the system.

While particular modeling methods have been presented and reviewed in numerous publications, reviews that consider combinations of methods are far scarcer. Combining different models brings both challenges and advantages, which we attempt to highlight through a systematic review of work that has involved this combined use. We thereby point to possible solutions that address the challenges and confer the benefits, offering orientation for future research. With constantly evolving and increasingly critical bioenergy systems, this study of combining the three modeling methods could be of timely assistance in identifying the potential pitfalls of existing energy systems. Furthermore, a marriage of these approaches may aid in further optimizing the systems from the technical, economic, and environmental perspective alike.

With this strong motivation to investigate past and current trends in combined-method modeling in the context of bioenergy and to present meaningful conclusion to inform future research, we set out to understand the issues of the biomass supply chain and the three modeling methods and conduct bibliometric analysis accordingly, by using headwords to find publications in the Scopus and Web of Science (WoS) databases, these being the largest and best-known scientific databases. We introduce the biomass context and our research methods below. After this, we analyze the findings and review the publications discussing use of two or more modeling methods to study the biomass supply chain. Discussion of bibliometric results and reviews is followed by suggestions for future actions.

1.1. The biomass supply chain

The typical supply chain system is a complicated logistics system composed of multiple activities [9,10]. The activities in the supply system are discrete processes that are distributed in space. A biomass supply system differs from traditional supply systems in that biomass is collected over vast territories, supply and demand both fluctuate, and the feedstock has to be treated before use [11]. The complexity of the supply chain is evident in nonlinearity and multi-scale behavior, the structure of the system spans several levels, and the system evolves and organizes itself through its functions and structures [12].

Biomass supply system may be divided into specific activities that are needed if biomass is to reach the end-use point from the point of origin. These activities, conceptualized in terms of the main groups shown in Fig. 1 [10,13], are highly interconnected, and decision

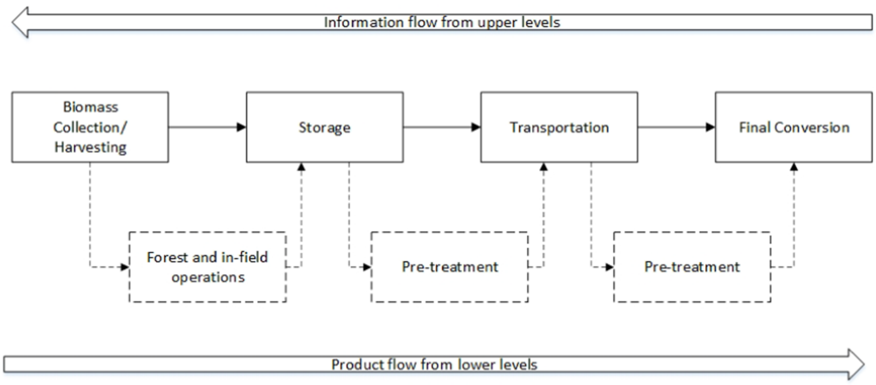

Fig. 1. A graphical depiction of the main activities in the biomass supply chain.

upstream in the chain affect various activities downstream [10]. Since the various activities change in accordance with the end product required, the raw material available, and the structure of the chain, it can be challenging or even impossible to find the optimal solution.

Because the biomass supply chain is a wide web, such tools as GIS are utilized to study the spatial distribution of the biomass supply. This is important since logistics costs in biomass supply tend to be high [14–16]. With several sources of material and numerous applications being available for biomass processing, the supply system is even more spatially dispersed, creating greater reason to use GIS in studying biomass supply systems [17–19]. In contrast, DTS models focus on the temporal aspect of a biomass supply system. This is important for examining the effect of interconnections and the timeliness of the various logistics elements. Finally, LCA has found popularity as interest has grown in the environmental impact associated with biomass supply, since, for example, biomass used to substitute fossil fuels can have a negative impact. Though biomass is less harmful, on account of its sustainability and the fact that is use reduces gaseous emissions of pollutants [10], dedicating land to biomass may be ecologically harmful and in some scenarios might even compromise food security [20]. Also, transporting biomass feedstock to processing facilities could lead, in some cases, to higher total greenhouse-gas (GHG) emissions than produced by conventional use of fossil fuels [21].

1.2. Geographic information systems

A GIS is a system for the production, management, analysis, and presentation of information that can be localized in a spatial environment. These systems are able to synthesize data from many geospatial information sources for visualization or analysis, as needed (Visual representation by GAO (2012) [22] as Fig. 2). The first computer-driven systems of this nature were implemented in the 1960s [23], and since then GIS infrastructure development has been closely connected with the development of computing hardware and software [24]. The 1990s saw the introduction of GIS in research into biomass supply and transportation, where the methods were brought to bear primarily for ascertaining the economic costs of biomass supply logistics [19,25,26]. Later, the scope of such studies was extended such that aspects additional to monetary economy – e.g., land-use changes and environmental impacts of biomass-handling – were taken into account [27].

One key technological advance in the GIS sphere has been the development of route calculation features, which are important in a logistics context. It was clearly impossible for such algorithms as Dijkstra's shortest path [28] and other work on the vehicle routing problem (VRP) [29], presented in the 1950s, to be widely applied before the processing capacity of standard computers reached a level satisfactory for this. Also, development from command-line programs to applications based on a graphical user interface (GUI) and, later, enhanced cartography obviously increased the attractiveness of GIS in biomass supply studies. Modern GIS applications support several standards for data transfer between external systems, and this compatibility has increased the opportunities for them to be used in parallel or together with other computer-driven study frameworks [21].

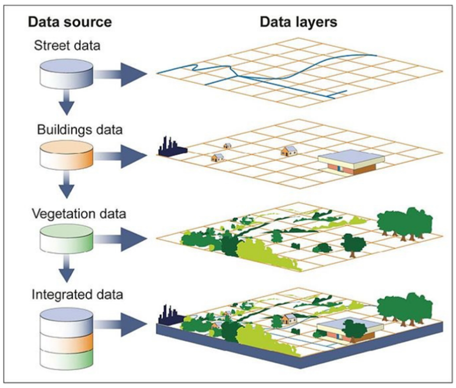

Fig. 2. A visual representation of incorporating data with GIS approach [22].

1.3. Discrete-time simulation

Dynamic simulations take into account temporal variation, in various ways. System dynamics and ordinary differential equations (ODE) are examples of modeling methods that operate in continuous time, whereas discrete-time simulation uses time steps, with a change in the system represented as occurring only set points in time. The DES and ABM approaches are widely used DTS methods in logistics studies [30,31]. It is worth noting that simulation methods, DTS among them, do not by nature include optimization; rather, results from simulation scenarios are compared in pursuit of near-optimal results [30]. Optimization may be part of a comparison phase that involves mathematical programming or heuristic methods.

DES describe the behavior of the complex system under study by considering events in sequential order. In this, the entities are passive objects that travel through blocks in a flowchart [32]. In DES, the system can be thought of as a network of queues and servers [33]. Researchers have improved on DES methods ever since the 1960s, when it was first presented for general-purpose system simulation [34]. ABM is more novel discrete-time simulation method then DES. The novelty of ABM has led to problems with terminology: the literature lacks universally accepted definitions that identify the fundamental concept of ABM and its assumptions [35]. While the first publications referring to a study method that could be classified as ABM were published relatively early, in 1971 [36], the method has developed vastly since then and can still be considered young.

ABM is suited well to describing activities of individuals and how they interact with each other. With regard to biomass, a supply-system agent might be a truck, harvester, biomass processor, or user of biomass. Some have suggested that ABM method is a suitable replacement for DES, even though DES has a large user base and may be better for some study settings [37]. For instance, because individuals make decisions both independently and in interaction with each other, ABM demands more computing power than DES does. In addition, the models tend to take longer to develop in ABM, rendering it a less attractive choice of study method in certain quarters [33].

In both methods of DTS, a modeling expert must create the model, and the modeler should be an expert in the subject under study too, so that the model logic is guaranteed to be valid [38]. This cannot always be achieved, so the model may have to be validated by a separate individual who is an expert in the field being modeled. The two main methods, DES and ABM, possess similarities, with it having been said that all ABM models are a combination of DES and ABM in operations research [37].

1.4. Life-cycle assessment

Life-cycle assessment is a technique developed to assess and address the possible impacts of products or services on the environment. It can be used to identify any opportunities to improve the environmental performance of a product or service at any phase in its life cycle, and it can be used also as a tool for decision-makers' use in strategic planning, decision-making, and product design aimed at improving the environmental performance of said product or service. One way of employing LCA is as a marketing tool, for any product or services, such that consumers can make an informed decision about their choice of product.

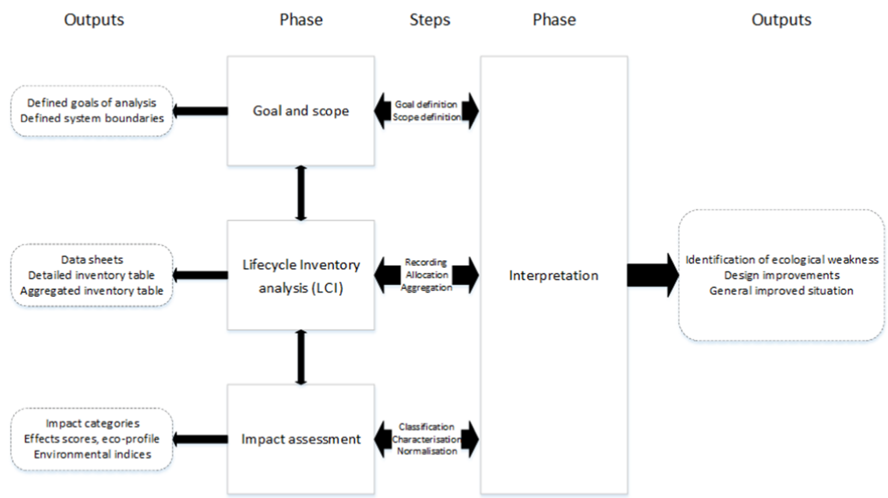

Fig. 3. The phases of LCA, including the individual steps and outputs.

LCA is a systematic process that begins with defining the system's boundaries in accordance with the goal of the project. In the second phase an inventory is taken of the process input and outputs that fall within the boundaries delineated. During the impact-assessment phase, the data collected in the inventory phase are correlated with the respective environmental implications that may exist. Finally, in the interpretation phase, the results from assessment of impact are interpreted and discussed, conclusions are formed, and recommendations are made on the basis of the goal set in the first phase. The four major phases of LCA and the steps defined for it are presented graphically in Fig. 3 [39].

LCA has been used for estimating consumer products' environmental impact ever since the 1960s, and the International Organization for Standardization (ISO) has been involved in LCA since 1994 [40,41]. In the context of energy-system analyses, LCA is considered to be among the best methods for identifying environment impacts and opportunities for improvement, although several issues have been acknowledged as strongly influencing the results [42,43]. Recently, bioenergy has come under scrutiny for its environmental performance in comparison to other green energy sources even though bioenergy does offer clear benefits over traditional fossil fuels such as coal. Accordingly, governments around the world apply various environmental policies that have motivated bioenergy organizations to assess the environmental benefit of their products on dimensions such as reduction of GHG emissions [42].

2. Materials and methods

In our survey of publications that refer to using computation-based methods for biomass supply chain analysis, we queried the Thomson Reuters bibliographic database WoS and Elsevier's Scopus database because the two differ substantially in coverage while both being commonly used for bibliometric analysis [44]. To obtain the most useful result sets, we constructed queries specific to each database and for each of the three modeling methods in turn. Hence, the queries yielded six distinct sets of publications for analysis, with hits from the publication title, keywords, and/or abstract. Sometimes authors use different terms for a given concept or refer to a keyword subclass alone, with the result that their paper might not be found by a query for only the more commonplace term or one relying on main classes alone, such as "biomass." To mitigate this effect, the queries were constructed to include several known general terms for the main class and also subclasses.

To find as many publications as possible addressing biomass supply chain analysis with computational methods, the queries featured three parts, referring to biomass, referring to the supply chain, and referring to the method. For each of these three elements, we used a list of headwords (see Table 1) that were composited with the Boolean operator OR. These three parts were combined with the Boolean operator AND. The headwords feature some use of parentheses, asterisks for wildcard matches, and quotation marks. Quotation marks were used to limit the results to matches for the exact multi-word search phrase rather than permit inclusion of spurious matches based on a single word. The use of asterisks was confined to the end of a word, to allow for several suffixes to be included in the search.

WoS and Scopus differ in their syntax for search queries; hence, we needed to build two versions of the query for each of the lists (the full set of queries is presented in the supplementary materials). The queries have brackets so that the search sequence works as intended: it is

Table 1
Headwords of the queries.

Description of biomass	Description of Supply chain	Description of method
Biomass	"Supply chain"	**GIS**
Bioenergy	"Supply system"	"Geographical information system"
Biofuel	"Supply network"	GIS
Bioethanol		"Spatial analysis"
Biodiesel		"Spatial statistic"
Biogas		
"Energy wood*"		**LCA**
"Forest fuel"		"Life cycle assessment"
"Wood chip*"		LCA
Woodchip*		"Life cycle analysis"
"Wood waste"		"Lifecycle assessment"
"Pellet*"		
"Energy Crop*"		**DTS**
"Sugarcane"		"Agent-based"
"Agricultural waste"		"Discrete-event"
"Municipal solid waste"		"Multi-agent simulation"

important for the OR operator to be processed before the AND operator. While the queries do not include document-type restrictions, we included only articles in the results considered, and, to have a better basis for comparison, only those articles published in 2018 or earlier were selected for analysis. The analysis included all the results listed from the queries. Articles addressing use of multiple methods together were found by comparing titles and authors in the list.

3. Results

Of the 498 publications returned via the search queries, Scopus included 312 and WoS included 364 (160 publications were found in both databases). The modeling method for which the most publications were found was LCA, with 335 records. Modeling based on GIS had the second-highest number of hits, with 98 records, of which 10 publications were also on the LCA list and one was on the DTS list. The modeling method for which the fewest publications were found was DTS, with 44 publications, one of which dealt with GIS also and 6 dealt with LCA. No publications on using all three modeling methods were found. The publication counts and their breakdown by modeling method and between the databases are shown in the Venn diagram provided as Fig. 4.

The oldest publications found [45], from 2000, was unique to the Scopus GIS list. The oldest publications for LCA [46] dated from 2004, and by the next year three further articles dealing with LCA were published. The earliest DTS article found [47] was published in 2006. As for articles on use of modeling methods in combination, the earliest one found [48] was from 2009 and addressed joint use of DTS and LCA. The distribution of articles reflects the recent increase in popularity of computational modeling methods, with LCA proving to be the most frequently used modeling method in studies of biomass supply chains as of 2018 (see Fig. 5). The breakdown of the publications found features only one article, if any, per year on a combination of methods, apart from 2017 and 2018. For 2017 there were four distinct publications in which a combination of methods was reported upon, and there were six in 2018. Later, upon closer examination, it was noted that three of the publications from 2017 and five from 2018 had been added to the results on the basis of automatically generated keywords.

The papers found were scattered over 140 journals, although *Journal of Cleaner Production* articles accounted for the largest number of them, 68 publications in all, with LCA publications accounting for the vast majority of these, 54 articles. This journal also ran two of the modeling-method-combining publications [25,49]. Most publications on GIS modeling came from the journal *Biomass and Bioenergy*, with 15 of the 98 GIS publications found. Finally, the largest number of DTS-based publications came from *Applied Energy*, at six publications. That said, there were 24 LCA articles and 10 GIS publications in that journal, making DTS the least commonly used modeling method in work presented in *Applied Energy*.

As noted above, some of the results were yielded via a set of keywords that the Scopus and WoS service generated themselves rather than author-supplied keywords. As was visible upon later inspection, the auto-generated keywords did not always accurately describe the paper. Also, it is possible that some publications on modeling-based methods or even on combinations thereof were not found, on account of the terms used diverging from the headwords we specified.

4. Discussion

4.1. Approaches combining LCA and GIS

The searches yielded 10 publications with headwords for LCA and GIS in the abstract, title, and/or keyword list. Six of these pieces were found on account of WoS and Scopus adding auto-generated keywords for the papers in question. Some of articles did reported upon a combination of GIS and DTS, rendering these added keywords justified but some cases did not.

That said, Marzullo et al. (2018) [50] studied water ecotoxicity footprints via LCA and GIS. While this 2018 work did involve a combination of the two methods, a keyword denoting biomass was automatically added and supply chains were not considered in this work.

One publication not to refer to GIS was a paper by Chaplin-Kramer et al. (2017) [51], who referred instead to spatial modeling. For this article, they applied it to account for the heterogeneous usage of land and thereby manage the problem that using average values for a region in LCA leads to inaccuracies in determination of the environment effects of the land-use change arising from increased demand. The authors' method supplements certain values from the life-cycle inventory and replaces others, to get the LCA to encompass spatial analysis. They called this method "Land Use Change Improved" LCA, or LUCI -LCA. The results from their case study illustrate considerable differences between conventional LCA and LUCI-LCA, thereby demonstrating the importance of taking into account spatial variation. Their conclusions stress the import of considering spatial elements when conducting land-use change studies and that the results for ecosystem impact must be translated into decision-ready information through predictive, system-scale, robust modeling.

Mirkouei et al. (2017) [52] too did not use any headwords for GIS section in their title, abstract, or keywords, even though GIS was used to analyze transport distances and the spatial distribution of forest biomass. They focused largely on multi-criteria decision-making, using the results as input to LCA involving mobile and stationary refineries in the bio-refinery supply chain. In the background to their work, these authors referred to various quantitative assessment methods, among them GIS, simulation with cost calculations, and operative research. The paper concludes with benefits for decision-makers, a proposed framework, and ideas for further research (including multiyear analysis) along with benefits to society from such work.

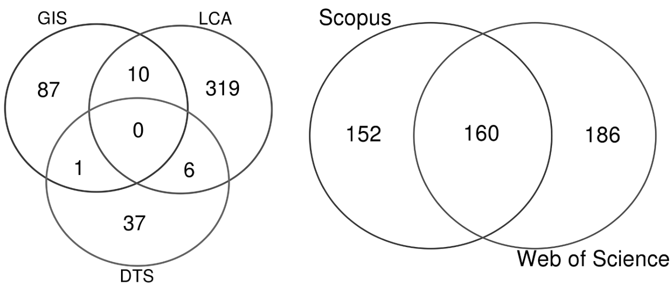

Fig. 4. A Venn diagram of the publications found.

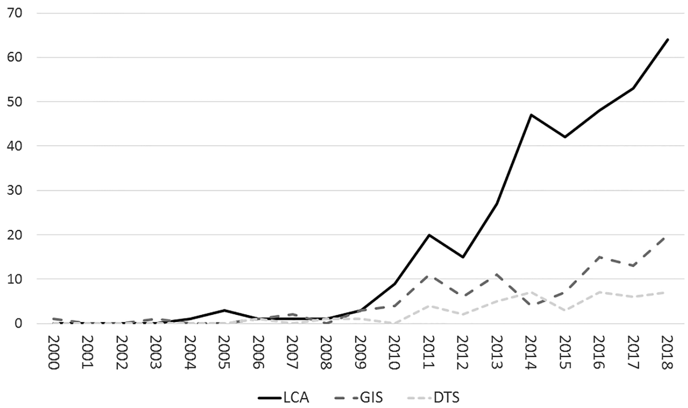

Fig. 5. The articles found, by year of publication.

Three publications from 2018 did have the LCA keyword added. Furubayashi and Nakata (2018) [53] used GIS to determine transportation paths for estimating emissions from biomass co-firing, but the estimations were from an energy-consumption expressions and no LCA was described in the publication. Santibañez-Aguilar et al. (2018) [54] employed GIS methods to determine viable facility locations for use in the relevant supply chain on the basis of residual biomass. Again, LCA was not used. Finally, Kesharwani et al.'s study (2018) [55], for which keywords for LCA and GIS were generated automatically at database level, did involve employing LCA to study total emissions of the supply chain, but the method as presented does not actually use it (GIS is not mentioned, though the locations of the facilities are in latitude and longitude).

Singlitico et al.'s (2018) paper [56] featured GIS- and LCA-related headwords, but LCA was mentioned only as the next stage in the research. The authors conducted GIS analysis to estimate waste and residue potential in Ireland, but LCA had not yet been implemented.

The oldest paper to be found with regard to LCA and GIS method was by Jäppinen et al. [57]. They analyzed the small-diameter energy wood supply chain in Finland, comparing three distinct supply methods. The authors used GIS material to examine the feedstock availability and transportation network, and LCA was conducted on the basis of the results from GIS analysis – transportation distances and road types were taken as input values for estimation of the GHG emissions of the scenarios studied. Using GIS solves the problem of using average values in small-scale analysis. The authors found that significant GHG reductions in biomass supply could be achieved in regions with poor road networks could be achieved by serving outlying parts of the supply area around a given demand point with transportation by rail from areas near a train loading station in another supply area. This shows the importance of spatial analyses when LCA is being carried out for a biomass supply chain at local scale.

Jäppinen et al. performed another study combining LCA and GIS methods [58]. As with the one described above, GIS was used to analyze feedstock availability and transport networks. This study examined three possible locations for a bio-refinery, with two separate scenarios. This led to larger numbers of results, which were reported via diagrams and vast swaths of numbers accompanied by copious explanation in the body text and in the figure caption and axis labels. The concluding section of the paper emphasizes the need to take into account feedstock combinations that allow for train or marine transportation options.

The newest paper found for which LCA and GIS headwords were supplied by the authors was published in 2017 by Sánchez-García et al. [25], who used GIS analysis to find the optimal location for a hypothetical power plant and applied LCA to estimate GHG emissions. The case study, set in Spain, involved wood chips produced from eucalyptus stems as the fuel. Three levels of feedstock availability were defined via GIS analysis, which was used also to determine transportation distances. The output values were fed in to LCA to ascertain the GHG emissions of the hypothetical power plant for each of several supply-chain operations. The paper concludes with description of a method that may be used on a smaller scale with more specific data and that demonstrates additional advantages in informing relative spatial and temporal decisions on scale of local demand. The paper also notes a need to consider competing demand points in this kind of study.

It was evident that most studies that combined GIS and LCA have used GIS data in feedstock availability and transportation network analysis and taken these results as input to LCA. An exception to this is the study conducted by Chaplin-Kramer et al. (2017) [51] that improved on joint use of LCA with GIS, to estimate land-use-change-related emissions with higher spatial resolution. This method integrates the two models more than do the others, which only chain methods and translate results between them. Either way, when complicated methods are used and multiple scenarios are analyzed, reporting the results in an easily understandable way grows more challenging.

The authors often note that the information produced by these study methods aids decisions-makers by providing them with new information (e.g., Chaplin-Kramer et al. [51] and Mirkouei et al. [52]). The value of simulation and the need for taking into account temporal variation were mentioned too. The requirements cited for future research includes taking into account multiple demand points, performing multiyear analysis, and accounting for the possibility of other supply sources – such as transportation by railway or waterway. All of these can be incorporated into the study by means of DTS.

Since GIS is a powerful spatial optimization tool that provides the opportunity to include the transportation network in analysis in terms of actual driving distances and real-world locations of the entities under study, it has much to add to LCA studies that are location-specific. Especially in small regional studies, in which spatial variation has a greater impact, GIS improve the results and makes them specific to the region. While tying the result to the given region limits applicability, such specificity is important in decision-making. Articles bring up concern about static results, since the biomass supply chain is highly dynamic, so sensitivity analysis should be conducted to mitigate this. A range of results, with different initial values, can imitate dynamic changes in the system.

4.2. Approaches combining LCA and DTS

Our search queries found six publications with an LCA and a DTS headword in the abstract, title, and/or keyword list. For three of these articles, the LCA keyword was added by WoS or Scopus. One of the publications was by Zhang et al. (2016) [59], study in which a multi-agent simulation was used to study various scenarios for the biomass supply chain. The study did not use LCA, so it is unclear to us why WoS added the corresponding automatically generated keyword. Yazan et al. (2017) [60] used ABM to study production of biogas from manure. While these authors noted the importance of GHG emissions, their description of results refers to neither emissions nor LCA. The last article with an added keyword was piece by Kishita et al. (2017) [49] on using DES to study the effect of the feed-in tariff applied to Japan for the adoption of woody biomass. Since the paper explicitly mentions life-cycle simulation (LCS) and the study did involve LCA, adding the keyword was justified.

Kishita et al. (2017) [49] study used DES for analyzing long-term (20-year) effects, with temporal uncertainties included, for a woody-biomass-fueled power generation plant. They used LCA to study CO_2 emissions, and the ISO 14044 standard was used to specify as the analysis unit the amount of wood consumed per year. The authors listed the advantages and disadvantages of the method. They cited the advantages of providing a narrative storyline via quantitative analysis, aiding in decision-making, and being able to be developed for all ways of converting biomass for energy use. Disadvantages cited were the use of annual averages in the model, omission of the ripple effect of the actions, and utilization of CO_2 emissions alone as indicative of environment aspect. The author noted the importance of the scenario selection also. Since the storyline is created on the basis of the set of scenarios chosen and they are compared only with each other, well-justified selection of scenarios is important.

Although these authors of Kishita et al. (2017) [49] did not include an LCA-linked headword in their abstract, title, or keyword list, their work did combine DTS and LCA study methods. The case studied was clearly explained, but that was less true of the combination of methods. For LCS, the authors referenced another study, done by Umeda et al. (2000) [61], and the source of LCA data was identified as one database providing initial values for the simulation. Still, the study shows that DES and LCA can be applied jointly in scenario-based analysis of the biomass supply chain wherein economic and environmental sustainability are determined.

The earliest article returned from the queries for DTS and LCA combined was published in 2009, on a study conducted by Davis et al. (2009) [48]. They took advantage of similarities between LCA and ABM to integrate LCA into ABM. The paper presents, as proof of principle, a study case investigating bioelectricity production in the Netherlands. Before presenting their proof of principle, the authors go through advantages of integrating LCA into the approach and address the limitations to such integration. The method expands the LCA matrix to provide corresponding values for input that agents use from a database or other agents in the model. Because this expansion makes the matrix larger, inversion of the matrix is computationally expensive. To circumvent this problem, Davis et al. (2009) [48] used an algorithm to perform the inversion and applied simplified LCA to evaluate climate change on the basic emissions.

The model used in the study case dealt with only two scenarios, and the case study was presented superficially. Sensitivity analysis involved running 100 simulations, leading to 100 results, which were examined via bar charts. These results were only a subset of the data gathered from the simulations, and it is noted in the paper that even this subset may be interpreted differently. The authors pointed out, as we do, that current LCA models are linear and ABM could provide spatial differentiation and dynamic aspects. Furthermore, the combination of ABM and LCA could have important implications for uncertainty analysis. Although uncertainty analysis is vital for balanced interpretation of a study, the linear and static nature of LCA creates problems in this regard; however, ABM could provide a solution to this problem, since it is a dynamic tool.

In a paper published by Halog and Manik (2011) [62] proposed a framework to integrate LCA, multi-criteria decision-making, ABM, and system dynamics into a hybrid model. Their report goes through all of this method's advantages and disadvantages, including the benefits conferred by hybrid thinking. Although the framework is described in detail, the authors did not utilize, for example, a case study, so the work is only theoretical in nature. The paper concludes by presenting multiple endeavors (e.g., research at the energy–environment–society nexus, novel energy-productions adaptations, and engaging the public in efforts to understand issues of sustainability and energy) that could be explored via the hybrid model described as the framework.

A 2015 publication featuring headwords related to LCA and DTS was authored by Bichraoui-Draper et al. (2015) [63]. The authors referred to agent-based life-cycle analysis (AB-LCA) for their method that uses ABM to complement LCA. Their method and case study are focused more on LCA. The model was developed as a modular structure, so that it would be easy to expand later. The paper examines the effect of economic, environmental, and social factors for the adoption of switchgrass as a biomass-based fuel. A case study of switchgrass-based ethanol production was used alongside reference values of 1800 GJ electricity generation from coal or natural gas with use of 10,000 L of fuel. The model was described in line with the ODD protocol [64], developed specifically for describing agent-based models.

The study presents vast quantities of LCA data via two matrices of figures. This method makes it easy to see how particular attributes affect environment impacts. While the study addressed only CO_2 emissions and did not consider emissions from land use, the authors conclude their paper by presenting extension possibilities – for instance, using GIS methods to consider real-world spatial information, such as yields and transportation distance from farm to refinery.

From the studies introduced above, it can be noted that there is strong motivation for using an LCA– DTS combination to support decision-making. With DTS, researchers gain the ability to compare effects between specific decisions, and LCA indicates the emissions connected with each respective decision. By accounting for temporal variation, DTS gives LCA a more dynamic nature.

Studies of the integration of bioenergy-related LCA and DTS have turned out to be rare. This might be because dynamic simulation is typically employed for decision-making on a certain process or well-bounded system while LCA is popular for considering consequences of life-cycle of product. At the same time, it might be that, since today's LCA modeling is relatively simple and linear in structure, it would be challenging to integrate ABM into LCA.

4.3. Approaches combining GIS and DTS

Kim et al. (2018) [65] wrote the only publication we found on combining GIS and DTS. In 2018, they presented a two-phase simulation method to allocate optimal locations for biomass storage facilities. The first phase used a process-based model, the Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC), to estimate switchgrass yields on the basis of weather and location data, with GIS utilized to achieve this. In the second phase, ABM was applied to take into account dynamic activities in the supply chain. This phase too involved GIS, for estimation of transportation times.

The authors noted that challenges arose during optimization: the computation burden increased, and assumptions were applied in order to reduce it (e.g., considering only three actors in the transportation-cost optimization and decreasing the required optimization performance when a larger number of zones was considered).

The authors concluded that their model achieved realistic locations for biomass storage facilities that accounts for the details of crop growth and supply-chain activities. For finding better locations for storage of biomass, the authors proposed modeling supply-chain activities in more detail and pointed to a need for concrete performance data, for validation of the model.

4.4. Combinations of LCA, GIS, and DTS

Although many combination-related publications conclude that the third method can be used to improving modeling, no work using all three modeling methods could be found. There are many challenges to be overcome for including all three methods. One is that experts in all three methods are needed for developing the model. Co-operation becomes more challenging whenever further participants are added, and costs rise also. Combining methods also creates a need for more assumptions, and increased uncertainties in the model may compromise the validity of the modeling. This challenge is emphasized in that the assumptions have to be compatible across all the methods, and those applied for each method have to be factored in before that method's results are taken as input to another method. To overcome this challenge, much work is needed: interest in developing LCA, GIS, and DTS combination models must increase, and there has to be demand for such integrated models in research and industry alike.

4.5. Combinations of methods in general

It can be noted, from publications on combined modeling methods, that there are numerous challenges in getting two or more modeling methods to work together. Among these are increased computational load, complicated validation of the models, and a need for huge quantities of data.

All modeling methods use different initial data, and combining methods demands large datasets. At the moment, various databases are available that could be used to develop a model that combines the three general modeling methods. Further development of these databases is valuable for the individual methods and for combination methods but also to improve validation of the models. There is a possibility of using assumptions and estimates to reduce the quantities of initial data necessary, but this lowers the accuracy of the model and both increases the importance of validation and complicates conducting it.

Computing power is available in abundance, but optimization of the computing operations still is needed if we are to overcome inordinate requirements when combining the models. This is achievable by improving each of the modeling methods separately and developing different methods to combine methods, finding advantages in particular ways of combining them. Opportunities can be found for using algorithms and well-founded assumptions to lower the computational load.

With all the challenges mentioned above, sometimes combining methods would be ill-advised. In these cases, other ways to add the benefits of the other methods may be examined, such as using stochastic distributions to include uncertainty in the model as Santibañez-Aguilar et al. (2018) [54] did in their study. One example of including emission estimation was supplied by Furubayashi and Nakata (2018) [53], who used mathematical expressions for energy consumption. Expressions of this kind are less demanding of computation power and are easier to use than a complicated model would be.

There are cases wherein combining methods improves a study to such an extent that it is highly advisable, and some integrated methods are not as challenging as others. For example, transportation distances yielded by GIS methods can be produced with ease and then added to DTS or LCA models along with the other initial values. This improves the models by giving them more localized and detailed variables. Adding DTS to a study, in turn, enables including temporal aspects that are important in a dynamic supply system. When combining models, one should consider how detailed all the constituent models have to be. At least the main one should be detailed enough to display proper accuracy, but a supporting model that works in less detail can be reasonable in some circumstances.

Applying one method and chaining it to other modeling methods for the next stage is, as Singlitico et al. (2018) [56] declared in their publication, one way to combine modeling methods. This permits the computation load to be divided, and reporting on the stages' results separately, in two publications, prevents excessively long reports. Thereby, the research might more readily remain coherent.

4.6. Results of the bibliometric analysis

It is easy to see that interest in computational methods is increasing: use of all three methods has risen lately. This development is clearest for LCA, on which we found nine articles published in 2010 and a full 64 in 2018. There are several factors in why more studies are now utilizing computational methods. One reason is the lower-cost and more powerful computing resources now available to researchers. Also, the software that is used in carrying out these studies has advanced and become more user-friendly. While computation-based methods hold great promise, it is particularly important, as their use increases, for the researcher to keep the validation and verification of the method transparent. In this regard, LCA has paved the way: standardized reporting is used in LCA, eliminating black boxes in the studies and rendering reports more comparable throughout the field.

It is worth highlighting that our queries did not find all publications in the field that dealt with combinations of methods. For example, Viana et al. (2010) [66], Karttunen et al. (2013) [67], and Jäppinen et al. [68] made joint use of GIS and DTS methods, but either these publications were not in the databases or the search terms did not match their details. This may well be true of work combining all three methods also. However, because we worked with two large peer-reviewed publication databases and a good-coverage headword list, conclusions can be drawn reliably from the results.

As the most commonly used of the three approaches, LCA has generated solid terminology and reporting practices, for which those using all other methods should strive. Terminology varies greatly with all those methods. Hence, complicated search queries were required for finding most of the publications on them, and any researcher wishing to find publications on a particular method would face the same problem. With novel methods such as computational modeling, some of the terms used are unknown even to experts in the field. While automatic generation of keywords helps to some extent, sometimes a keyword picked out was, as we indeed saw in our work, unjustified. It is authors' responsibility to make sure their keywords represent the paper correctly. If two modeling methods are used, it is recommendable to mention both in the abstract and include terms referring to both in the keyword list.

This brings us back to the importance of consistent terminology. It would make specifying keywords easier for authors and searchers alike. Kishita et al. (2017) [49] used the term "life cycle simulation," or "LCS," to denote all simulation methods. A more precise notion, agent-based life-cycle analyses (AB-LCA), was used by Bichraoui-Draper et al. (2015) [63]. This choice of term focuses on ABM in particular, although LCA is generally associated with life-cycle assessments rather than analyses. Self-explanatory terms such as these two should enter standard public use for all the methods and combinations thereof. When GIS is brought in, the word "spatial" can be added readily to that for the other methods, as Hauscild and Potting (2006) [69] did with the term "Spatial Differentiation in Life Cycle Impact Assessment." Umbrella terms may also be useful, so long as they are well-established. In this paper, DES and ABM both were referred to as DTS methods to distinguish these from other dynamic simulation methods, such as system dynamics or ODE simulations. Though uniform terminology in the field would be ideal, we recognize that establishing this may take a long time. Hence, alternative approaches to improve communications between modelers and researchers should be considered and developed.

While we did not find publications reporting on use of all three methods in combination, incorporating an additional method into studies was often mentioned in the proposed future research directions. Another common conclusion was that modeling can support decision-makers. This is understandable, since modeling-based methods enable examination of planned and hypothetical entities, thereby giving unique insight into the effects of decisions not yet made. Because all of the methods rely heavily on scenarios and comparative analyses, there are many aspects of the results to report. This may lead to hard-to-follow reporting, which draws attention to the need for devoting greater effort to establishing uniform and systematic reporting for all the individual modeling methods and combination of them. The same thing could be said on reporting on the models themselves, but this has been recognized, and standards and protocols have been developed accordingly. Alongside the ISO standards for LCA [70,71] that guide authors in reporting on the models and results, ABM has the aforementioned ODD protocol [64] for reporting on the model, although the protocol does not address how the results should be reported. While researchers are waiting for more sophisticated and appropriate instructions for this reporting, it should remain as transparent and precise as possible. Describing the model by referencing previous publications should be avoided, since access to earlier articles describing it may be limited. One option is to describe the model in supplementary material, to keep the paper more concise and focused on the subject of study.

5. Conclusions

Interest in the use of mathematical computational methods has increased, and this trend only seems to be continuing. A corresponding upsurge can be seen specifically in the use of geographic information systems, life-cycle assessment, and discrete-time simulation for modeling and in applying combination of the associated models. With growing computing power and the need to include more detail and address more extensive subjects of study, the models have gained complexity. These wider study cases and the complex models employed for them must be explained clearly when the results are published. To achieve this, a consistent manner of reporting needs to be established. Also, for greater visibility of the relevant publications, it should be ensured that searches find them via self-evident, uniform methods. It would both facilitate searches and be to the authors' benefit to have coherent terminology in place that is suitable for the various modeling methods. Finally, our work enabled us to conclude that combining the classes of method offers the ability to take more variables into account, thereby improving the results of modeling-based studies. Better results benefit researchers, decision-makers, and operation managers alike, by putting more reliable information at their disposal.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2019.03.201.

References

[1] Pegden CD, Sadowski RP, Shannon RE. Introduction to simulation using SIMAN. 2nd ed. New York, NY, USA: McGraw-Hill, Inc.; 1995.

[2] De Meyer A, Cattrysse D, Rasinmaeki J, Van Orshoven J. Methods to optimise the design and management of biomass-for-bioenergy supply chains: A review. Renew Sustain Energy Rev 2014;31:657–70. https://doi.org/10.1016/j.rser.2013.12.036.

[3] Awudu I, Zhang J. Uncertainties and sustainability concepts in biofuel supply chain management: A review. Renew Sustain Energy Rev 2012;16:1359–68. https://doi.org/10.1016/j.rser.2011.10.016.

[4] Sharma B, Ingalls RG, Jones CL, Khanchi A. Biomass supply chain design and analysis: Basis, overview, modeling, challenges, and future. Renew Sustain Energy Rev 2013;24:608–27. https://doi.org/10.1016/j.rser.2013.03.049.

[5] Wang L, Agyemang SA, Amini H, Shahbazi A. Mathematical modeling of production and biorefinery of energy crops. Renew Sustain Energy Rev 2015;43:530–44. https://doi.org/10.1016/j.rser.2014.11.008.

[6] Ghaderi H, Pishvaee MS, Moini A. Biomass supply chain network design: An optimization-oriented review and analysis. Ind Crops Prod 2016;94:972–1000. https://doi.org/10.1016/j.indcrop.2016.09.027.

[7] Keramati A, Eldabi T. Supply chain integration: modelling approach. Res Rev Proc Eur Mediterr Middle East Conf Inf Syst. 2011.

[8] Winston WL, Goldberg JB. Operations research: applications and algorithms. Belmont: Thomson Brooks/Cole; 2004.

[9] Rentizelas AA, Tolis AJ, Tatsiopoulos IP. Logistics issues of biomass: The storage problem and the multi-biomass supply chain. Renew Sustain Energy Rev 2009;13:887–94. https://doi.org/10.1016/j.rser.2008.01.003.as.

[10] Allen J, Browne M, Hunter A, Boyd J, Palmer H. Logistics management and costs of biomass fuel supply. Int J Phys Distrib Logist Manag 1998;28:463–77. https://doi.org/10.1108/09600039810245120.

[11] Zandi Atashbar N, Labadie N, Prins C. Modelling and optimisation of biomass supply chains: a review. Int J Prod Res 2017:1–25.

[12] Surana A, Kumara S, Greaves M, Raghavan UN. Supply-chain networks: a complex adaptive systems perspective. Int J Prod Res 2005;43:4235–65. https://doi.org/10.1080/00207540500142274.

[13] Toka A, Iakovou E, Vlachos D. Biomass supply chain management for energy polygeneration systems. Proc 1st Olympus Int Conf Supply Chain. 2010. p. 1–2.

[14] Gonzales D, Searcy EM, Ekşioğlu SD. Cost analysis for high-volume and long-haul transportation of densified biomass feedstock. Transp Res Part A Policy Pract 2013;49:48–61. https://doi.org/10.1016/j.tra.2013.01.005.

[15] Laitila J, Asikainen A, Ranta T. Cost analysis of transporting forest chips and forest industry by-products with large truck-trailers in Finland. Biomass Bioenergy 2016;90:252–61. https://doi.org/10.1016/j.biombioe.2016.04.011.

[16] Laitila J, Lehtonen E, Ranta T, Anttila P, Rasi S, Asikainen A. Procurement costs of cereal straw and forest chips for biorefining in South-East Finland. Silva Fenn 2016;50. https://doi.org/10.14214/sf.1689.

[17] Voivontas D, Assimacopoulos D, Koukios EG. Assessment of biomass potential for power production: a GIS based method. Biomass Bioenergy 2001;20:101–12. https://doi.org/10.1016/S0961-9534(00)00070-2.

[18] Liang T, Khan MA, Meng Q. Spatial and temporal effects in drying biomass for energy. Biomass Bioenergy 1996;10:353–60. https://doi.org/10.1016/0961-9534(95)00112-3.

[19] Noon CE, Daly MJ. GIS-based biomass resource assessment with BRAVO. Biomass Bioenergy 1996;10:101–9. https://doi.org/10.1016/0961-9534(95)00065-8.

[20] Smith P, Haberl H, Popp A, Erb K, Lauk C, Harper R, et al. How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals? Glob Chang Biol 2013;19:2285–302. https://doi.org/10.1111/gcb.12160.

[21] Jäppinen E, Korpinen O-J, Laitila J, Ranta T. Greenhouse gas emissions of forest bioenergy supply and utilization in Finland. Renew Sustain Energy Rev 2014;29:369–82. https://doi.org/10.1016/j.rser.2013.08.101.

[22] GAO. Geospatial information: OMB and Agencies Need to Make Coordination a Priority to Reduce Duplication (GAO-13-94); 2012.

[23] Chrisman N. Charting the unknown: How computer mapping at Harvard became GIS. Esri Press; 2006.

[24] Tomlinson RF. Thinking about GIS : geographic information system planning for managers; 2013.

[25] Sánchez-García S, Athanassiadis D, Martínez-Alonso C, Tolosana E, Majada J, Canga E. A GIS methodology for optimal location of a wood-fired power plant: Quantification of available woodfuel, supply chain costs and GHG emissions. J Clean Prod 2017;157:201–12. https://doi.org/10.1016/j.jclepro.2017.04.058.

[26] Zhang F, Johnson DM, Sutherland JW. A GIS-based method for identifying the optimal location for a facility to convert forest biomass to biofuel. Biomass Bioenergy 2011;35:3951–61.

[27] Malczewski J. GIS-based land-use suitability analysis: a critical overview. Prog Plann 2004;62:3–65.

[28] Dijkstra EW. A note on two problems in connexion with graphs. Numer Math 1959;1:269–71. https://doi.org/10.1007/BF01386390.

[29] Dantzig GB, Ramser JH. The truck dispatching problem. Manage Sci 1959;6:80–91. https://doi.org/10.1287/mnsc.6.1.80.

[30] Becker M, Wenning B-L, Görg C, Gehrke JD, Lorenz M, Herzog O. Agent-based and discrete event simulation of autonomous logistic processes. Borutzky W, Orsoni A, Zobel R, editors. ECMS 2006 Proc. vol. 571. ECMS; 2006. p. 566–71. https://doi.org/10.7148/2006-0566.

[31] Windisch J, Väätäinen K, Anttila P, Nivala M, Laitila J, Asikainen A, et al. Discrete-event simulation of an information-based raw material allocation process for increasing the efficiency of an energy wood supply chain. Appl Energy 2015;149:315–25.

[32] Borshchev A, Filippov A. From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. 22nd Int Conf Syst Dyn Soc 25-29 July 2004. 2004. p. 45.

[33] Maidstone R. Discrete Event Simulation, System Dynamics and Agent Based Simulation: Discussion and Comparison. 2012; 1–6.

[34] Gordon G. A general purpose systems simulation program. Proc December 12-14, 1961, East. Jt Comput Conf Comput - Key to Total Syst Control New York, NY, USA: ACM; 1961. p. 87–104. https://doi.org/10.1145/1460764.1460768.

[35] Schieritz N, Milling PM. Modeling the forest or modeling the trees A comparison of system dynamics and agent-based simulation. Proc 21st Int Conf Syst Dyn Soc. 2003.

[36] Schelling TC. Dynamic models of segregation. J Math Sociol 1971;1:143–86.

[37] Siebers P-O, Macal CM, Garnett J, Buxton D, Pidd M. Discrete-event simulation is dead, long live agent-based simulation!. J Simul 2010;4:204–10.

[38] Sargent RG. Verification and validation of simulation models. Proc 2009 Winter Simul Conf IEEE; 2009. p. 162–76. https://doi.org/10.1109/WSC.2009.5429327.

[39] Matthews J, Parr C, Araoye O, McManus M. Environmental auditing of a packaging system for redesign: a case study exploration. J Clean Energy Technol 2014:267–73. https://doi.org/10.7763/JOCET.2014.V2.138.

[40] Guinée JB, Heijungs R, Huppes G, Zamagni A, Masoni P, Buonamici R, et al. Life cycle assessment: past, present, and future. Environ Sci Technol 2011;45:90–6. https://doi.org/10.1021/es101316v.

[41] McManus MC, Taylor CM. The changing nature of life cycle assessment. Biomass Bioenergy 2015;82:13–26. https://doi.org/10.1016/j.biombioe.2015.04.024.

[42] Cherubini F, Strømman AH. Life cycle assessment of bioenergy systems: State of the art and future challenges. Bioresour Technol 2011;102:437–51. https://doi.org/10.1016/j.biortech.2010.08.010.

[43] Cherubini F, Bird ND, Cowie A, Jungmeier G, Schlamadinger B, Woess-Gallasch S. Energy- and greenhouse gas-based LCA of biofuel and bioenergy systems: Key issues, ranges and recommendations. Resour Conserv Recycl 2009;53:434–47.

https://doi.org/10.1016/j.resconrec.2009.03.013.
[44] Mongeon P, Paul-Hus A. The journal coverage of Web of Science and Scopus: a comparative analysis. Scientometrics 2016;106:213–28. https://doi.org/10.1007/s11192-015-1765-5.
[45] Sørensen B, Meibom P. Global renewable energy scenario. Int J Glob Energy Issues 2000;13:196–276.
[46] Arena U, Mastellone ML, Perugini F, Clift R. Environmental assessment of paper waste management options by means of LCA methodology. Ind Eng Chem Res 2004;43:5702–14. https://doi.org/10.1021/ie049967s.
[47] Sokhansanj S, Kumar A, Turhollow AF. Development and implementation of integrated biomass supply analysis and logistics model (IBSAL). Biomass Bioenergy 2006;30:838–47. https://doi.org/10.1016/j.biombioe.2006.04.004.
[48] Davis C, Nikolić I, Dijkema GPJ. Integration of life cycle assessment into agent-based modeling. J Ind Ecol 2009;13:306–25. https://doi.org/10.1111/j.1530-9290.2009.00122.x.
[49] Kishita Y, Nakatsuka N, Akamatsu F. Scenario analysis for sustainable woody biomass energy businesses: The case study of a Japanese rural community. J Clean Prod 2017;142:1471–85. https://doi.org/10.1016/j.jclepro.2016.11.161.
[50] Marzullo R de CM, dos S Matai PHL, Morita DM. New method to calculate water ecotoxicity footprint of products: A contribution to the decision-making process toward sustainability. J Clean Prod 2018;188:888–99. https://doi.org/10.1016/J.JCLEPRO.2018.03.307.
[51] Chaplin-Kramer R, Sim S, Hamel P, Bryant B, Noe R, Mueller C, et al. Life cycle assessment needs predictive spatial modelling for biodiversity and ecosystem services. Nat Commun 2017;8. https://doi.org/10.1038/ncomms15065.
[52] Mirkouei A, Haapala KR, Sessions J, Murthy GS. A mixed biomass-based energy supply chain for enhancing economic and environmental sustainability benefits: A multi-criteria decision making framework. Appl Energy 2017;206:1088–101. https://doi.org/10.1016/j.apenergy.2017.09.001.
[53] Furubayashi T, Nakata T. Cost and CO_2 reduction of biomass co-firing using waste wood biomass in Tohoku region, Japan. J Clean Prod 2018;174:1044–53. https://doi.org/10.1016/J.JCLEPRO.2017.11.041.
[54] Santibañez-Aguilar JE, Flores-Tlacuahuac A, Betancourt-Galvan F, Lozano-García DF, Lozano FJ. Facilities location for residual biomass production system using geographic information system under uncertainty. ACS Sustain Chem Eng 2018;6:3331–48. https://doi.org/10.1021/acssuschemeng.7b03303.
[55] Kesharwani R, Sun Z, Dagli C. Biofuel supply chain optimal design considering economic, environmental, and societal aspects towards sustainability. Int J Energy Res 2018;42:2169–98. https://doi.org/10.1002/er.4006.
[56] Singlitico A, Goggins J, Monaghan RFD. Evaluation of the potential and geospatial distribution of waste and residues for bio-SNG production: A case study for the Republic of Ireland. Renew Sustain Energy Rev 2018;98:288–301. https://doi.org/10.1016/J.RSER.2018.09.032.
[57] Jäppinen E, Korpinen O-J, Ranta T. The effects of local biomass availability and possibilities for truck and train transportation on the greenhouse gas emissions of a small-diameter energy wood supply chain. Bioenergy Res 2013;6:166–77. https://doi.org/10.1007/s12155-012-9244-9.
[58] Jäppinen E, Korpinen O-J, Ranta T. GHG emissions of forest-biomass supply chains to commercial-scale liquid-biofuel production plants in Finland. GCB Bioenergy 2014;6:290–9. https://doi.org/10.1111/gcbb.12048.
[59] Zhang X, Luo K, Tan Q. A feedstock supply model integrating the official organization for China's biomass generation plants. Energy Policy 2016;97:276–90. https://doi.org/10.1016/j.enpol.2016.07.027.
[60] Yazan DM, Fraccascia L, Mes M, Zijm H. Cooperation in manure-based biogas production networks: An agent-based modeling approach. Appl Energy 2018;212:820–33. https://doi.org/10.1016/J.APENERGY.2017.12.074.
[61] Umeda Y, Nonomura A, Tomiyama T. Study on life-cycle design for the post mass production paradigm. Artif Intell Eng Des Anal Manuf 2000;14:149–61. https://doi.org/10.1017/S0890060400142040.
[62] Halog A, Manik Y. Advancing integrated systems modelling framework for life cycle sustainability assessment. Sustainability 2011;3:469–99. https://doi.org/10.3390/su3020469.
[63] Bichraoui-Draper N, Xu M, Miller SA, Guillaume B. Agent-based life cycle assessment for switchgrass-based bioenergy systems. Resour Conserv Recycl 2015;103:171–8. https://doi.org/10.1016/j.resconrec.2015.08.003.
[64] Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF. The ODD protocol: A review and first update. Ecol Modell 2010;221:2760–8. https://doi.org/10.1016/j.ecolmodel.2010.08.019.
[65] Kim S, Kim S, Kiniry JR. Two-phase simulation-based location-allocation optimization of biomass storage distribution. Simul Model Pract Theory 2018;86:155–68. https://doi.org/10.1016/J.SIMPAT.2018.05.006.
[66] Viana H, Cohen WB, Lopes D, Aranha J. Assessment of forest biomass for use as energy. GIS-based analysis of geographical availability and locations of wood-fired power plants in Portugal. Appl Energy 2010;87:2551–60. https://doi.org/10.1016/j.apenergy.2010.02.007.
[67] Karttunen K, Lättilä L, Korpinen O-J, Ranta T, et al. Cost-efficiency of intermodal container supply chain for forest chips. Silva Fenn 2013;47:24.
[68] Jäppinen E, Korpinen O-J, Ranta T. Simulation modelling in biomass logistics-benefits, challenges and three case studies. 23rd Eur Biomass Conf Exhib New York: ETA-Florence Renewable Energies; 2015. https://doi.org/10.5071/23rdEUBCE2015-1CV.3.9.
[69] Hauschild M, Potting J. Spatial Differentiation in Life Cycle Impact Assessment: A decade of method development to increase the environmental realism of LCIA. Int J Life Cycle Assess 2006;11:11–3. https://doi.org/10.1065/lca2006.04.005.
[70] SFS-EN ISO 14040. Environmental management – Life cycle assessment – Principles and framework (ISO 14040:2006); 2006.
[71] SFS-EN ISO 14044. Environmental management – Life cycle assessment – Requirements and guidelines (ISO 14044:2006); 2006.

Publication II

Korpinen, O-J., Aalto, M., Venäläinen, P., Ranta. T.
Impacts of a High-Capacity Truck Transportation System on the Economy and Traffic Intensity of Pulpwood Supply in Southeast Finland

Croatian Journal of Forest Engineering
Vol. 40(1), pp. 89–105, 2019.

Impacts of a High-Capacity Truck Transportation System on the Economy and Traffic Intensity of Pulpwood Supply in Southeast Finland

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Abstract

High-capacity transportation (HCT) of roundwood is a road transport concept that is currently being demonstrated in Finland and Sweden. In Finland, HCT trucks are in most cases unable to access roadside storages, but they are expected to bring cost savings in highway transportation between transshipment terminals and mill yards. Evaluating the optimal solutions is challenging due to the complexity of the transportation systems. This paper presents a dynamic simulation model, SimPulp, which was developed to generate information about the impacts of substituting HCT for a part of the present pulpwood transportation system. A case study in the area of the most intensive pulpwood use in Finland was conducted. The results indicate that HCT has potential for reducing transport costs and especially the traffic intensity of roundwood procurement in the studied area. The economic advantages of pulpwood HCT could be more significant in a larger area or in the use of inter-terminal backhauling.

Keywords: roundwood, supply chain, logistics, high-capacity transportation (HCT), decision support, simulation modelling, agent-based modelling (ABM)

1. Introduction

Enhancing the forest-industry logistics and transportation infrastructure was a central issue in the Strategic Programme for the Forest Sector in Finland, which was administered by the Ministry of Employment and the Economy (2012) in 2011–2015. An important target, which is gradually being fulfilled, was the increase in vehicles' carrying capacity in road transportation. In 2013, the maximum permissible gross weight of full-trailer trucks in Finland was raised from 60 t to 76 t with a precondition of modifications to the axles and cargo space (Government decree 407/2013). At present, 38% of trucks used in roundwood transportation fulfil the conditions of 68 t and 55% of trucks the conditions of 76 t maximum weight (Venäläinen 2017a).

The total cost savings due to the increased weight allowance can be considered significant because road transport represents 76% of all roundwood transportation in Finland, and trucks are also involved in rail and waterway transport chains (Strandström 2016). It has been estimated that at distances longer than 100 km, the average timber transport cost with a 76 t truck is circa 20% less than that of a 60 t truck (Venäläinen and Korpilahti 2015).

Currently, the Finnish Transport Safety Agency is investigating possibilities to allow high-capacity transportation (HCT) trucks on certain parts of the Finnish road network (Lahti and Tanttu 2016). By the end of the year 2017, there were five trucks in timber transportation and four trucks in wood chip transportation with a gross weight allowance higher than 76 tons (Finnish Transport Safety Agency 2017). During the experimental period, data from onboard recorders is collected to analyse fuel consumption in different conditions and vehicles' suitability for e.g. intense traffic flow or extreme weather. Identical recorders have been mounted on 76 t trucks to obtain comparable data from regular vehicles (Heinonen 2016).

Roundwood HCT has also been demonstrated with 90 t and 74 t trucks in Sweden (Asmoarp et al. 2018), where the maximum permissible gross weight has been recently raised to 74 t (Swedish Transport Agency 2018). At present, the greater weight allowance applies only on designated roads, mostly in Northern Sweden (Swedish Road Administration 2018), but in the future, the network is envisioned to cover also other roads currently permitted for 64 t trucks.

In Finland, most HCT trucks operate between terminals (Finnish Transport Safety Agency 2017). In timber transportation, this means that wood transshipment from regular trucks to HCT trucks takes place in an economically feasible location in the transportation system and the HCT truck delivers the wood to the mill. Transshipment can be done in different ways, e.g. directly from a regular truck onto an HCT truck, by trailer interchange, via a storage pile or with a mix of these methods. Also, special equipment, such as separate loading machines or demountable truck bodies, can be used to speed up the work (Fig. 1).

The HCT system is largely similar to intermodal systems that include truck transportation from roadside storages to the loading point of a train or a vessel. However, the number of potential locations for HCT terminals in a system is usually manifold. This is due to the extensive road network and relatively low establishment and maintenance costs of terminals in comparison with rail or port terminals (Iikkanen and Sirkiä 2011, Impola and Tiihonen 2011). HCT trucks are less liable to delays than trains and vessels, which are usually dependent on other traffic on single-track rail lines and narrow waterway passages (e.g. sluices).

In a feasibility analysis of HCT, the comparison with a conventional fleet should not include only the route between terminals. Instead, the overall performance of an HCT system should be assessed. Investigating the economic advantages, losses and break-even points of conventional and more advanced methods is a complex matter that includes uncertainty and case-specific variables. Many of the variables are not only location-dependent but also time-dependent because the balance of demand and supply varies over time.

In operations research, complex supply chains are usually studied with mathematical optimization or simulation models (Almeder et al. 2009). For example, backhaul systems in wood procurement have been previously studied with linear programming (LP) methods (e.g. Palander and Väätäinen 2005, Carlsson and Rönnqvist 2007), which are suited for cases where study problems and modelling elements can be generalized and aggregated to a high abstraction level. In such cases, empirical data from the vehicles are usually sufficiently available, and thus, model parameters are typically well known before the implementation of the model. Simulation models' primary purpose is not to find the optimal state of the system, but rather to increase understanding about causalities and interconnections for the implementation or development of real-world systems (e.g. Biswas and Narahari 2004).

This paper deals with the modelling of an HCT system with a holistic simulation approach. The paper presents the design of a dynamic simulation model, SimPulp, and a case study where the model has been implemented. The objective of the study was to assess the impacts of replacing a proportion of the present truck transportation system of pulpwood with an HCT system in Southeast Finland. The study was carried out by simulating the system in scenarios with varying numbers of vehicles and transshipment terminal locations. Economic indicators were used for assessing the performance of the vehicles, and transport intensity indicators were used for evaluating the impacts on the transportation network. The paper finishes with a discussion about the findings of the case study and further research needs arising from the output of SimPulp.

Fig. 1 Transshipment of pulpwood from regular trucks and terminal stock onto an HCT truck (5+5 axle full trailer, 84 t gross weight) equipped with a demountable truck body. Photo: Esa Hirvonen

2. Methodology

2.1 Model overview

SimPulp was designed to simulate operations in pulpwood transportation by road in a visualized spatial environment of two road transport networks: a regular network and an HCT corridor network. Other transport modes than road, i.e. rail and waterway transportation, were not modelled in detail but they were included as factors affecting the truck transportation system.

The main principle of SimPulp is to fulfil the demand of pulp mills by delivering wood from roadside storages and intermediate terminals. The model produces performance data about the transport fleet operating in:

⇒ the existing road transportation system of pulpwood

⇒ a system including HCT and transshipment terminals.

This data will, thereafter, be used for e.g. economic and environmental impact analyses.

SimPulp was developed as an agent-based simulation model (ABM), which has been documented as a useful approach in studies of complex systems including spatially explicit geographical information (Crooks and Castle 2012). AnyLogic 7.2.0 Professional was used as the software for the design and development of SimPulp.

2.2 Agents and state variables

SimPulp includes five agent types: »Main«, »Demand Point«, »Supply Point«, »Vehicle« and »HCT Terminal«. All agent types have their own characteristics and populations (i.e. groups of individuals) in the model. »Demand Point« includes a population of points representing the pulp mills. The population of »Supply Point« represents groups of roadside storages in a small area (5×5 km grid cell) and transit points between the studied area and the surrounding area. »Vehicle« represents timber trucks and includes two populations representing regular and HCT trucks. The availability of trucks is modelled with state variables indicating whether the truck is reserved for an existing transport task or available for a new delivery. »HCT Terminal« contains the population of terminals required for pulpwood transshipment from regular trucks to HCT trucks. Pulpwood as transported goods is not represented by any agent or »entity« (specific to discrete-event modelling approaches) but by two values with which the agents communicate: the amount of wood (as double value) and wood type (as option list, i.e. pine, spruce or hardwood).

»Main« is the connecting platform for the interactions between all other agents. »Main« includes a linkage with the geographical information system (GIS), which is the environment for logistical actions of the agent populations. The »Demand Point«, »Supply Point« and »HCT Terminal« populations are stationary, while the geographic locations of the »Vehicles« population change over time. The visualization of the GIS environment includes a tiled background map and a road network with routing options, both provided by OpenStreetMap (AnyLogic Company 2017).

2.3 Source data and experiment setup

SimPulp requires a quantity of input datasets that initialize the model before each simulation run. The datasets are uploaded from spreadsheet tables containing the following information:

⇒ Dataset 1: Locations of demand points and their annual demand by wood type

⇒ Dataset 2: Locations of supply points and their annual supply by wood type

⇒ Dataset 3: Locations of HCT terminals

⇒ Dataset 4: Daily demand distribution (daily demand per annual demand) by wood type

⇒ Dataset 5: Daily supply distribution by wood type

⇒ Dataset 6: Distribution and variation of arriving trains at demand points

⇒ Dataset 7: Distribution and variation of arriving vessels at demand points

⇒ Dataset 8: Transport distances and transport times between supply points, demand points and HCT terminals

⇒ Dataset 9: Route ranking matrix according to supply costs from supply points.

The locations are given with WGS84 geographical coordinates. Two separate GIS analyses are required to produce the data for Dataset 8. Transport distances and times are calculated for regular trucks in the first analysis, and for HCT trucks in the second analysis. Dataset 9 includes all routing options from supply point to demand point, including routing via each HCT terminal.

In addition to the datasets, scenario-specific data is entered into SimPulp in the startup window. This data includes the number and transport capacities of regular and HCT trucks available, and terminals (from Dataset 3) that are selected for the simulation run.

2.4 Process overview

There are two pulpwood delivery methods: direct delivery from »Supply Point« to »Demand Point« and delivery from »Supply Point« to »Demand Point« via »HCT Terminal«. The first method involves only regular trucks. In the second method, both HCT and regular trucks participate. Regular trucks transport material between »Supply Point« and »HCT Terminal«, and HCT trucks transport material between »HCT Terminal« and »Demand Point«.

The main principle of operation is the following:

⇒ the supply point generates wood according to a given speed and time distribution (Dataset 2) and always offers wood to the demand points when a full truckload of wood becomes available. The offers are made in the order defined by Dataset 9

⇒ the demand point accepts the offer if its storage volume has not been exceeded

⇒ the supply point reserves an available truck for loading when the demand point accepts the offer

⇒ the truck returns to the same supply point, and if the supply point does not address a new task for the truck, the truck becomes available for all supply points.

Fig. 2 provides an overview of the whole process. The process is accomplished individually for each wood type. However, the same truck population is used for the transportation of all wood types. One truckload can include only one wood type at a time. Additionally, the population of »HCT Terminal« contains as many agents as there are possible transport destinations from each terminal location to each mill. This is because, regardless of the delivery method, wood is routed from the supply point across to the final destination and the truckloads routed to different mills cannot be mixed at the same terminal location.

HCT terminals behave like demand points when wood is offered to them and like supply points when wood is forwarded to demand points. Accordingly, a route including HCT is selected when the first location accepting the offer is an HCT terminal. By default, the demand point begins accepting offers after the storage at the demand point drops under 1/121 of the annual consumption (i.e. average demand of ca. three days) of the respective wood type, and stops accepting offers when the storage exceeds 1/52 of the annual consumption (i.e. average demand of one week). HCT terminals, serving the same demand point, reject offers if their total storage has exceeded 1/24 of the annual demand (i.e. average demand of ca. 1/2 months) for the respective wood type at the respective demand point. The terminals begin to accept wood again when the inventory drops below the threshold.

2.5 Generalization and system boundaries

SimPulp includes only the transportation system between supply points, demand points and transshipment terminals for HCT transportation. Forest operations (i.e. harvest and forwarding) and mill-yard operations (e.g. transfer from buffer storage to conveyor) are excluded from the model. SimPulp does not take into account different variations of transshipment methods at HCT terminals or different unloading methods of trucks and trains at pulp mills. The following standard time consumption parameters are used:

⇒ load truck at roadside or HCT terminal: 85 s/t

⇒ unload truck to the conveyor at demand point: 19 min/truck

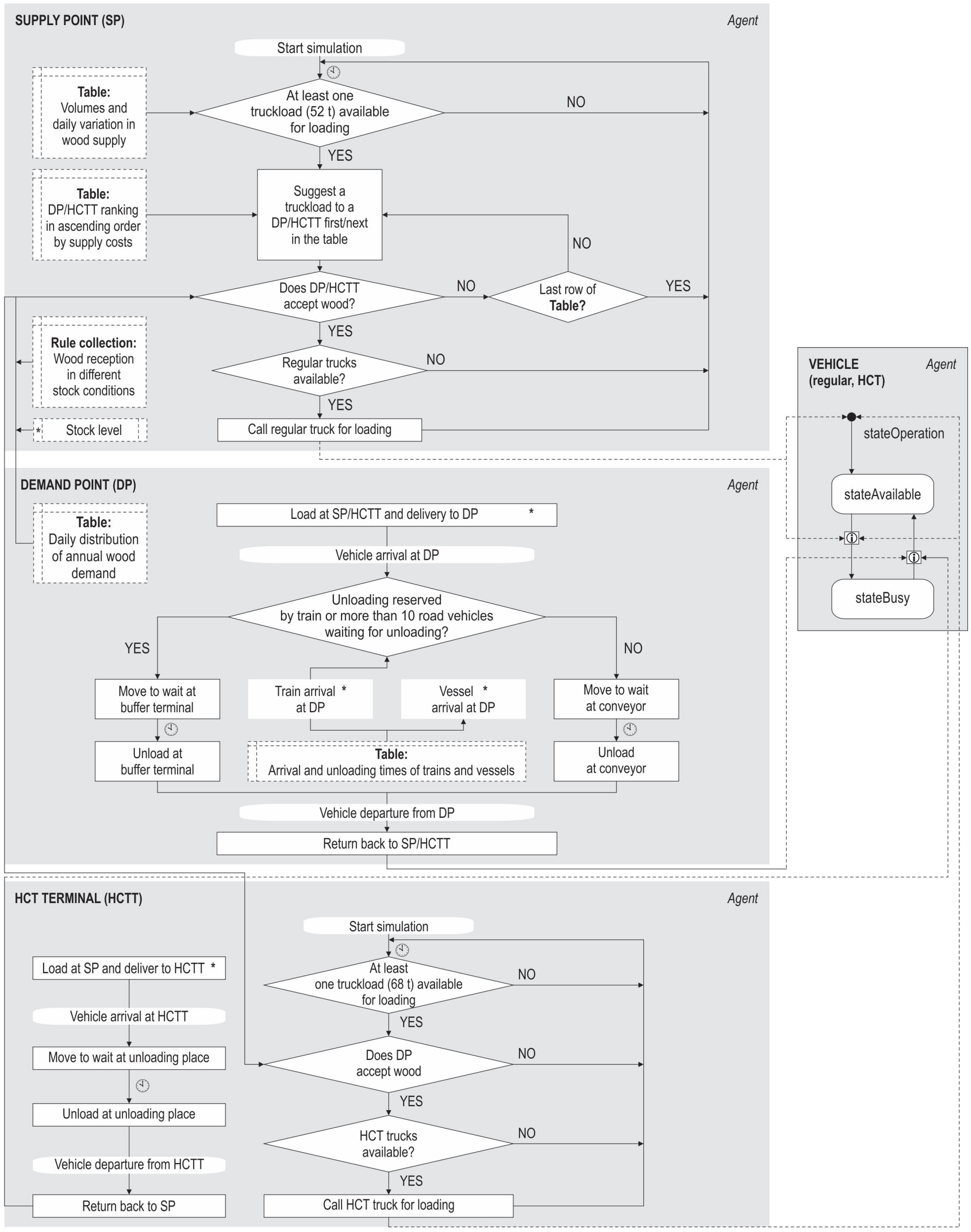
⇒ unload truck to HCT terminal or buffer terminal at demand point: 42.5 s/t

⇒ unload train or vessel at demand point: 30 s/t.

The transportation fleet includes regular trucks and HCT trucks with default payloads of 52 t and 68 t, respectively. Individual underweight deliveries or deliveries without a trailer, which are occasional for regular trucks in the real world (Venäläinen and Korpilahti 2015), cannot be included in SimPulp. The total haulage per truck is accumulated only from transport tasks, i.e. wood deliveries and empty returns, and transfers between wood supply regions or depots are not taken into account. Accordingly, time consumption and utilization rates of trucks are based only on the transport tasks and the time spent at supply points, demand points and HCT terminals. Other time (i.e. »stateAvailable« in Fig. 2) is not considered as utilization of the truck.

The geographical extent in SimPulp is not limited, but according to the test runs in different geographical areas, a large studied area with a plenitude of locations (supply points, demand points and HCT terminals) increases the computing time significantly. The resolution of the supply point grid should be adjusted according to the scale of the studied area and processing capacity of the hardware. We used a standard desktop PC with an eight-thread Intel processor of a 3.5 GHz clock speed and 32 GB RAM.

The map-based visualization of the system may look illogical if the model is applied in geographical regions with poor coverage of OpenStreetMap road data, for example sparsely populated areas in developing countries (Mooney 2015). This does not, however, affect the decision-making in SimPulp because the decisions are based on Datasets 8 and 9. Instead, GIS data used for the analysis producing Datasets 8 and 9 should be of a high quality.



* indicate the randomness related to the events and stopwatches possible time delays

Fig. 2 Decision-making process of the agents and agent communication in the SimPulp model

Table 1 Output types used for runtime evaluation of a simulation run

Subject	Model output	Unit	Subtype division	Presentation format
Vehicles	Available trucks	n	Regular, HCT	Time plot
	Vehicle utilization	%	Regular, HCT	Time plot
System performance	Pulpwood at supply points available for transport	t	Pine, spruce, hardwood	Time plot
	Pulpwood at demand-point stocks	t	Pine, spruce, hardwood	Time plot
	Accumulated pulpwood shortage at demand points	t	Pine, spruce, hardwood	Time plot
Pulp mills (Demand-point specific information)	Stock at demand point	t	Pine, spruce, hardwood	Time plot
	Stock at HCT terminals	t	Pine, spruce, hardwood	Time plot
	Accumulated costs	€	Direct deliveries, via HCT terminal Distance-based, time-based, terminal-based	Bar graph
HCT terminals (Terminal-specific information)	Pulpwood time in HCT terminal	d	Pine, spruce, hardwood	Histogram
	Available pulpwood in terminal	t	Pine, spruce, hardwood	Time plot

2.6 Warm-up, follow-up and initialization of simulation run

The simulation run lasts from 1 January 2015 to 31 December 2016. The first year from 1 January 2015 to 31 December 2015 is a warm-up period where no data is collected. The transportation system is assumed to be in steady state by 1 January 2016 when the data collection begins. The year 2016 is, therefore, called the follow-up period.

Before the start of the simulation run, the user enters the number of vehicles and their transport capacities and cost function constraints to the model. The user also enables or disables the HCT system in the experiment. If HCT system is enabled, the user also selects which HCT terminals from Dataset 3 are used for the experiment. After the start command, the input datasets are imported to the model and the simulation run begins. The first decision (Fig. 2) is made at the supply point when the accumulating supply volume at the supply point equals or exceeds one full truckload.

2.7 Random events

The accumulation of supply at supply points is based on annual supply volumes defined in Dataset 2 (point specific) and the daily proportions of the annual volumes defined in Dataset 5 (universal for all supply points). A random seed is used for each simulation run, and the random generator determines the time of the daily accumulation for each point. However, the accumulation is allowed to take place between 08:00 and 00:00 only. The arrival times of vessels and trains are also determined by the random generator. Time constraints and arrival probabilities are given in Datasets 6 and 7. For example, vessel arrivals can be disabled for the winter to match the conditions of the real world.

2.8 Model output

Output data from the simulation run is collected for runtime evaluation and post-run analysis. The data used in runtime evaluation is presented as graphical information, principally as time plots (Table 1). Vehicle utilization and system performance can be monitored at a general level, and the traffic at pulp mills and HCT terminals can be followed up individually. Together with the map-based presentation about trucks' movement in the system, runtime graphics are a useful way to validate and verify the model.

Data is exported to post-run analysis by five functions collecting data from the follow-up period. »Get terminal costs«, »Get utilizations« and »Get total supply« have a similar purpose as the output types in Table 1, and »Get route data« collects the number of routes travelled between all locations in the system. »Write to excel« sorts out the results of these functions and exports the data to a spreadsheet file.

3. Case study

3.1 Case overview

The case study focused on pulpwood transportation in Southeast Finland. The area comprises ca. 4%

of the Finnish land area, but its seven pulp mill locations consume almost 40% of the industrial pulpwood used in Finland (Natural Resources Institute Finland 2016). The volume of ca. 15.0 Mm³ over bark, consisting of 5.7 Mm³ of pine (*Pinus sylvestris*), 3.6 Mm³ of spruce (*Picea abies*) and 5.6 Mm³ of hardwood (mostly *Betula pendula, Betula pubescens* and *Populus tremula*), corresponds to the total net weight of ca. 12.8 Mt in transportation. The pulpwood consumption is largely dependent on wood imports from neighbouring regions (Natural Resources Institute Finland 2015a, 2015b). Especially large amounts of hardwood are imported from Russia (Finnish Customs 2016). Roundwood exports from the studied area are mainly other than pulpwood and, therefore, outbound deliveries from the area were not considered in the study.

3.2 Spatial analyses

The input data with geographical references resulted from spatial analyses where QGIS Desktop 2.10.1 and ArcGIS 10.3.1 software were used. In the first analysis, Dataset 8 was created by calculating driving distances and times of the shortest routes between all locations in the system. Two transport networks were used: a network for regular trucks and a network for HCT corridors. The analysis was based on the digital road network data Digiroad (Finnish Transport Agency 2015), documentation about temporary overweight transports (ELY Centre Pirkanmaa 2015) considered as potential HCT corridors and location data from Datasets 1–3. Driving speeds of regular trucks were acquired from the speed limits of Digiroad (Finnish Transport Agency 2015). For roads without speed limits, e.g. forest roads, the allowed speed of 20 km/h was used. Considering the fact that a truck is unable to maintain the allowed maximum speed constantly, a driving speed of 75% of the allowed speed was applied for regular trucks. Based on the recent experiences about pulpwood HCT operations in the studied area, a constant driving speed of 60 km/h was applied.

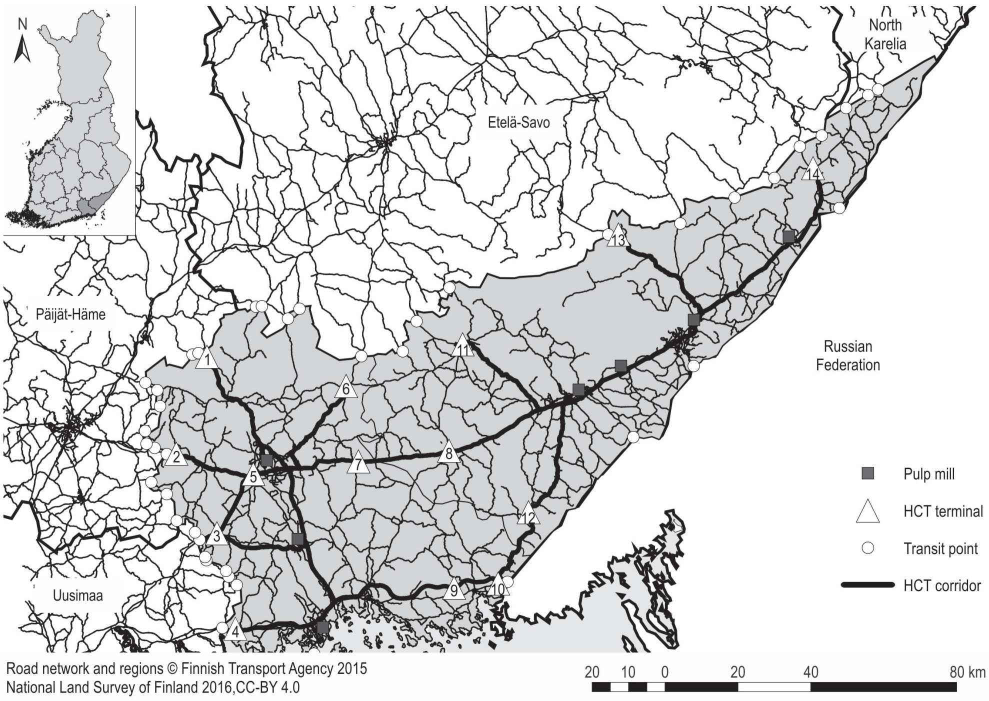


Fig. 3 The network of trunk roads in pulpwood transportation, pulp mills, potential HCT terminal locations and HCT corridors, and transit points between the studied area (grey) and the surrounding area

Table 2 Summary of location-specific input data used in the case study

Subject	Target Dataset (s)	Domain agent in SimPulp	Function in SimPulp	Data sources	Annual totals
Biomass availability	2, 5, 8	Supply Point	Represents wood supply at roadside storages and transit points	Estimated pulpwood harvest volumes in Finnish municipalities (Räsänen 2015) Biomass of growing stock per pulpwood type as 16×16 m grid (Natural Resources Institute Finland 2015c) Balance of industrial pulpwood removals and forest industries' pulpwood consumption by region in 2014 (Natural Resources Institute Finland 2015a, 2015b) Consumption of foreign pulpwood by region in 2014 (Natural Resources Institute Finland 2015a) Imported roundwood from Russia (Finnish Customs 2016) Border crossings of trucks (Finnish Customs 2016) Volumes of imported roundwood by transportation method in 2006–2015 (Strandström 2016)	Studied area: pine 0.8 Mt spruce 0.5 Mt hardwood 0.4 Mt Transit points: pine 1.2 Mt spruce 1.8 Mt hardwood 1.2 Mt Domestic 5.1 Mt transnational 0.7 Mt
Biomass demand	1, 3, 8	Demand Point	Represents pulpwood consumption at pulp mills	Industrial pulpwood consumption in 2015 (Natural Resources Institute Finland 2016)	Pine 4.9 Mt spruce 3.1 Mt hardwood 4.8 Mt
Transport networks	8	Main	Connect locations	Digital road network data, Digiroad (Finnish Transport Agency 2015) Network for overweight transports (ELY Centre Pirkanmaa 2015)	
Rail and waterway deliveries	6, 7	Demand Point	Affect truck transportation and stock levels at mills	Transport volumes of pulpwood deliveries by trains and vessels to mills (Finnish Transport Agency 2016, 2017, Finnish Customs 2016, Strandström 2016)	Pine 2.9 Mt spruce 0.8 Mt hardwood 3.2 Mt

Supply points (Dataset 2) included 491 centre points of a 5×5 km grid inside the studied area, representing roadside storages, and 41 transit points connecting the studied area to surrounding regions on the main road network. Four of the transit points were border-crossing points between Finland and Russia. An additional driving time of 80 min was assigned to the deliveries from transit points to represent the time consumption in neighbouring regions in Finland. For transit points between Finland and Russia, the extra time was 160 min. HCT terminals (Dataset 3) were positioned in 14 highway junctions attracting the majority of transport routes without HCT. This decision was based on visual examination of regular truck routes between supply and demand points in GIS. Fig. 3 presents the locations of HCT corridors, HCT terminals (Dataset 3), transit points and demand points (Dataset 1).

In the second analysis, Dataset 2 was accompanied by pulpwood volumes. The estimated annual supply in municipalities (Räsänen 2015) was allocated to the supply point grid in the studied area. The estimated pulpwood volume in the growing stock per wood type (Natural Resources Institute Finland 2015c) was used as a weighing factor for supply points located in the same municipality, and the disaggregation was conducted according to the method presented in previous studies about forest biomass availability and logistics (Jäppinen et al. 2013, Korpinen et al. 2013).

The assessment of the annual supply at transit points was based on the statistics about pulpwood removals and domestic pulpwood consumption in other regions of Finland (Natural Resources Institute Finland 2015a, 2015b, 2016), foreign pulpwood consumption in Southeast Finland (Natural Resources Institute Finland 2015a) and foreign trade and border traffic (Finnish Customs 2016). The estimation of train and vessel delivery volumes to the mills (Datasets 6 and 7) was based on information extracted from the Digitraffic database (Finnish Transport Agency 2016), foreign trade statistics (Finnish Customs 2016), waterway statistics (Finnish Transport Agency 2017) and a survey by Strandström (2016). The Digitraffic database was also used for assessing the train arrival intensity at the mills (Dataset 6). Vessels (Dataset 7) were assumed to arrive between April and November, and their arrival interval was constant at a monthly level but random within each month. The demand was assumed to be stable around the year (Dataset 4). Table 2 summarizes the datasets imported to SimPulp.

3.3 Cost data

The transportation cost data for Dataset 9 was based on the transport distance and time matrices of Dataset 8 and experimental cost-related data (e.g. fuel and wearing-part consumption, driving speeds and work shifts) that is being collected constantly from existing HCT trucks and their comparison trucks with regular weight. The following equations were fitted on the verified cost data from HCT trials between October 2014 and September 2017 (Poikela 2017):

$$CRT_{\mathrm{f\_mill}}=1.0816\,d^{0.957}+47.33\,t \quad (1)$$

$$CRT_{\mathrm{e\_mill}}=0.8127\,d^{0.943}+47.33\,t \quad (2)$$

$$CRT_{\mathrm{f\_term}}=1.0816\,d^{0.957}+47.65\,t \quad (3)$$

$$CRT_{\mathrm{e\_term}}=0.8127\,d^{0.942}+47.65\,t \quad (4)$$

$$CRT_{\mathrm{f\_mill}}=1.1833\,d^{0.961}+39.473\,d^{0.0283}\,t \;\big|\; d\geq 20 \quad (5)$$

$$CRT_{\mathrm{e\_mill}}=0.8176\,d^{0.944}+39.473\,d^{0.0283}\,t \;\big|\; d\geq 20 \quad (6)$$

Where:

CRT represents transportation costs of regular trucks
CHT transportation costs of HCT trucks
f_mill transportation with a full load to the demand point
e_mill return from the demand point with an empty load
f_term and *e_term* transportation between the supply point and HCT terminal with full and empty loads
d distance, km
t time (h) of the trip between the origin and the destination.

Since HCT has not been used often for very short trips in the trials, it was determined that *CHT* is valid only for trips of 20 km or longer. The formulas return the cost as euros per truck per trip.

The routes were ranked in ascending order by unit costs (€/t) for each supply point. The unit costs were calculated as follows:

$$C_{\mathrm{direct}}=\frac{CRT_{\mathrm{f\_mill}}+CRT_{\mathrm{e\_mill}}}{52} \quad (7)$$

$$C_{\mathrm{via\_term}}=\frac{CRT_{\mathrm{f\_term}}+CRT_{\mathrm{e\_term}}}{52}+C_{\mathrm{term}}+\frac{CHT_{\mathrm{f\_mill}}+CHT_{\mathrm{e\_mill}}}{68} \quad (8)$$

Where:

C_{direct} the cost on the direct route from the supply point to the demand point
$C_{\mathrm{via\_term}}$ the cost on the route via the HCT terminal
C_{term} the cost of the use of the HCT terminal, €/t.

3.4 Sensitivity analysis

The case study included uncertain issues, whose impact on the system output was examined in a sensitivity analysis. Such issues were:

⇒ the ratio of HCT trucks to regular trucks in the system
⇒ the impact of terminal costs on HCT utilization
⇒ the impact of a transition to a sparser network of HCT terminals.

The sensitivity analysis focused principally on the economic output of the system, but attention was also paid to the utilization rates of regular and HCT trucks.

The impact of varying terminal service costs was studied, as there were very few references from similar pulpwood transportation systems available. In road-to-rail transshipment, an average transshipment cost of € 0.90/t was earlier reported (Iikkanen and Sirkiä 2011), but without any details about how much is based on truck drivers' labour costs and how much on the terminal fixed costs. The impact of truck visits (including loading and unloading) at terminals was included in the cost functions (Eqs. (3–6)), but the expenses from the maintenance of the terminal network were not. The cost of using an HCT terminal (i.e. C_{term} in Eq. (8)) was estimated at € 0.50/t as the baseline assumption. There are, however, several case-specific factors behind the economic basis of biomass terminals, such as land value or groundwork needs (e.g. Impola and Tiihonen 2011, Kühmaier et al. 2016, Virkkunen et al. 2016), and the cost impact on the logistics could also be higher. On the other hand, terminal costs can be compensated by possible benefits of HCT that were not considered in the study, such as lower organization costs or more efficient collection of roadside storage remainders (Venäläinen 2017b). To account for this uncertainty, two alternatives to the baseline value, € 0.00/t and € 1.00/t, were included in the analysis.

There are about 1300 timber trucks in Finland, and truck transportation of 5.8 Mt in the case corresponds with 13% of timber-truck transportation in the country (Strandström 2016). Based on the fact that SimPulp excludes depot time and supply area transfers, it was assumed that a suitable transport capacity would equal 100–150 regular trucks in the model. Three alternatives for the total transport capacity (TTC) were selected: a) 7800 t, b) 6500 t, and c) 5200 t. The alternatives correspond to the total payload of 150, 125 and 100 regular trucks, respectively.

Since regular trucks are needed to access the roadside storages in any case, it was estimated that HCT would be reasonable for less than 50% of the transport tasks, and HCT truck proportion of TTC was set to vary between 10% and 40%. Alternatives of 0, 20, 30 and 40 HCT trucks were applied to the scenarios of 7800 t TTC, and alternatives of 0, 10, 20 and 30 HCT trucks were applied to other TTC scenarios. The remaining TTC was complemented with regular trucks so that TTC was fully met (Fig. 4).

The impact of HCT terminal reduction was studied to determine the importance of terminal network coverage. This was done by removing terminals 1, 4, 5, 7, 8, 9, and 10 (Fig. 3) from the network. The selection was done with the same transport intensity based allocation method as the selection of the original 14-terminal network. Terminal utilization was recorded by the total volume of wood flown through the terminal, and the economic impact was assessed by comparing total costs with the cost output of the corresponding scenario with 14 terminals.

3.5 Scenario qualification

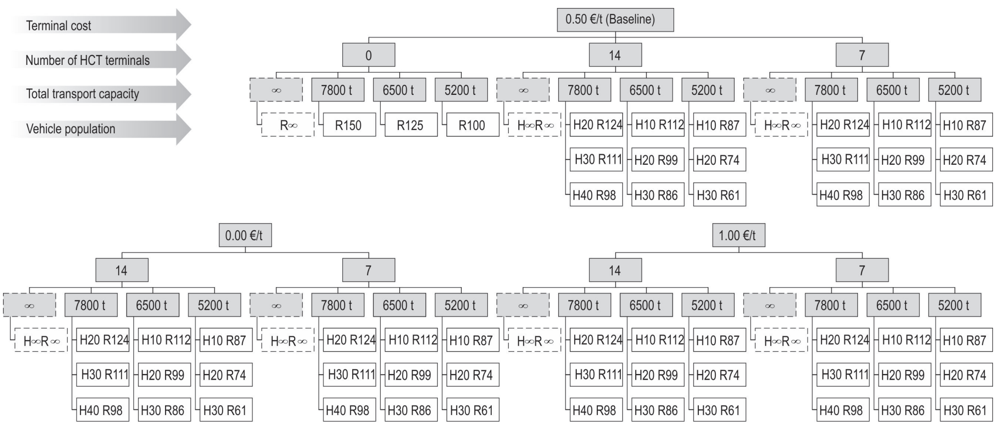
The scenarios were qualified or disqualified on the basis of accumulated wood shortage within the follow-up period. Due to the random events in the model, the follow-up period starting from a dynamic situation, and the fact that the model is just a generalization from the real world, a minor wood shortage was anticipated to be acceptable. Reference scenarios with an unlimited number of trucks were included to confirm that the unfulfilled demand in qualified scenarios was not caused by an insufficient number of trucks. If demand fulfilment was in accordance with the reference scenario, it was presumed that the system was sufficiently in balance to enable equitable comparison between the scenarios. The deviation from the reference scenario was indicated by rates of fulfilled total demand (FTD) and unfulfilled demand per wood type (UFD). It was determined that if the FTD of the scenario was over 0.5 percentage units smaller than the reference, or if the UFD of any wood type deviated more than 2 percentage units from the reference, the scenario was disqualified.

To make scenario outputs comparable, the transport distances and costs were readjusted by the difference between the targeted (i.e. 5.8 Mt) and simulated total haulage.

4. Results and discussion

4.1 Scenario qualifications

The scenario qualification returned 38 qualified scenarios corresponding to a TTC of 6500 t or 7800 t (Table 3). All 19 scenarios of a 5200 t TTC were disqualified based on their poor FTD and UFD ratings, indicating that the transport capacity corresponding to 100 regular trucks is inadequate against the transportation needs. In the qualified scenarios, the UFD principally consisted of hardwood shortage, while all wood types were represented in the UFD of the disqualified scenarios. The scenario of 150 regular trucks resulted in a slightly higher FTD (99.1%) than the scenario of 125 regular trucks (98.6%). In the corresponding HCT



Legend:
Fields with an unbroken outline indicate scenarios included in the qualification
Fields with a dashed outline indicate reference scenarios of an unlimited vehicle population
H – number of HCT trucks
R – number of regular trucks

Fig. 4 Configuration of simulation scenarios (white fields) scenarios, 7800 t scenarios produced an FTD of 98.1% and 6500 t scenarios an FTD of 97.9% on average.

The impact of terminal cost variation on the system balance was marginal. The average FTD was 98.0% in the scenarios with a terminal cost of € 0.50/t and 98.1% with costs of € 0.00/t and € 1.00/t. In contrast, the increase of the HCT proportion in the fleet seemed to decrease the average FTD slightly within the group of 6500 t. In this group, the average FTDs with 10, 20 and 30 HCT trucks were 98.2%, 97.9% and 97.7%, respectively.

4.2 Transport distances and costs

The total transport distances were shorter in all scenarios including 14 HCT terminals than in the corresponding scenario without HCT (Fig. 5 and 6). The greatest savings in total distances, i.e. 12.6–14.1%, were caused by the scenarios including the highest proportion of HCT trucks. Direct transportation to the mills represented at most 50% of the total distances in these scenarios. The group of 6500 t resulted in ca. 3% shorter transport distances on average than the TTC of 7800 t.

In the scenario group of 14 HCT terminals, transport costs were lower in 13 scenarios and higher in 5 scenarios than the costs of the corresponding scenario without HCT. The scenarios including 20 HCT trucks were the most profitable when no terminal cost was applied. When the terminal cost of € 0.50/t or € 1.00/t was applied, the most economic HCT scenarios had

Table 3 Fulfilled total demand (FTD) and unfulfilled demand (UFD) per wood type (pine–spruce–hardwood) in simulation scenarios

HCT terminals, n	HCT trucks, n	Regular trucks, n	HCT proportion of total transport capacity, %	Total transport capacity, t	€ 0.50/t (Baseline)		Terminal costs, € 0.00/t		€ 1.00/t	
					FTD, %	Wood type UFD, %	FTD, %	Wood type UFD, %	FTD, %	Wood type UFD, %
–	–	∞	–	∞	99.0*	0–0–3*	–	–	–	–
–	–	150	–	7800	99.1	0–0–3	–	–	–	–
–	–	125	–	6500	98.6	0–0–4	–	–	–	–
–	–	100	–	5200	96.1	5–3–4	–	–	–	–
14	∞	∞	–	∞	97.9*	0–1–6*	97.8*	1–1–6*	98.0*	1–1–5*
14	20	124	17	7808	98.1	1–1–5	98.2	0–1–5	98.1	0–1–5
14	30	111	26	7812	98.1	1–0–6	98.3	0–0–5	98.0	1–1–5
14	40	98	35	7816	97.7	1–1–6	98.4	0–1–5	98.1	1–1–5
14	10	112	10	6504	98.2	1–1–5	98.4	1–0–4	98.0	1–1–5
14	20	99	21	6508	98.0	1–1–5	97.9	1–1–6	98.5	0–0–5
14	30	86	31	6512	98.0	1–1–5	97.5	2–1–5	97.6	2–1–5
14	10	87	13	5204	95.1	6–3–5	95.6	6–3–4	94.9	7–3–6
14	20	74	26	5208	96.4	4–2–6	96.7	4–1–6	96.6	4–2–6
14	30	61	39	5212	90.4	10–9–10	91.2	9–8–10	88.0	13–12–11
7	∞	∞	–	∞	97.6*	2–1–6*	98.1*	1–1–5*	97.8*	0–1–6*
7	20	124	17	7808	98.3	0–1–5	98.1	1–1–5	98.0	1–1–5
7	30	111	26	7812	97.9	1–1–5	98.1	1–0–5	98.2	0–1–5
7	40	98	35	7816	98.2	0–1–5	98.0	1–0–6	98.4	0–0–5
7	10	112	10	6504	97.8	1–1–6	98.4	1–1–4	98.3	0–1–4
7	20	99	21	6508	98.0	1–1–5	97.6	1–1–6	97.6	2–1–6
7	30	86	31	6512	97.6	2–1–6	97.9	1–1–6	97.8	2–1–4
7	10	87	13	5204	95.6	6–2–5	95.1	7–3–6	95.5	6–2–5
7	20	74	26	5208	96.7	3–2–6	96.0	4–2–7	96.6	4–2–5
7	30	61	39	5212	88.9	9–12–13	90.3	10–9–12	86.5	13–13–15

* Reference scenario with unlimited transport capacity

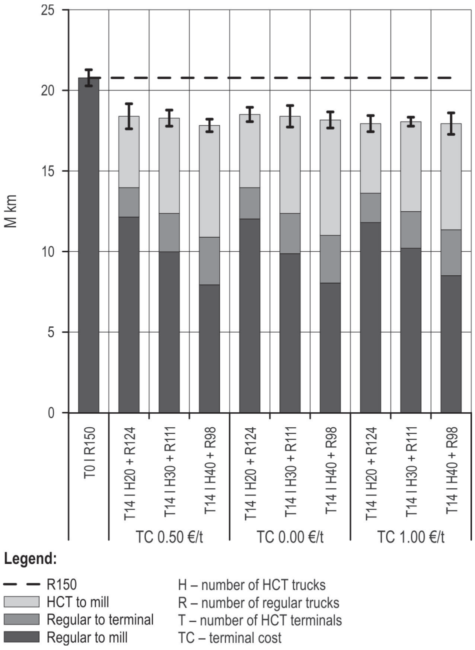


Fig. 5 Transport distances including empty returns according to transport modes in scenarios of 7800 t total transport capacity and 0 or 14 HCT terminals. Error bars represent the range of total transport distances in 8 reproduced simulation runs

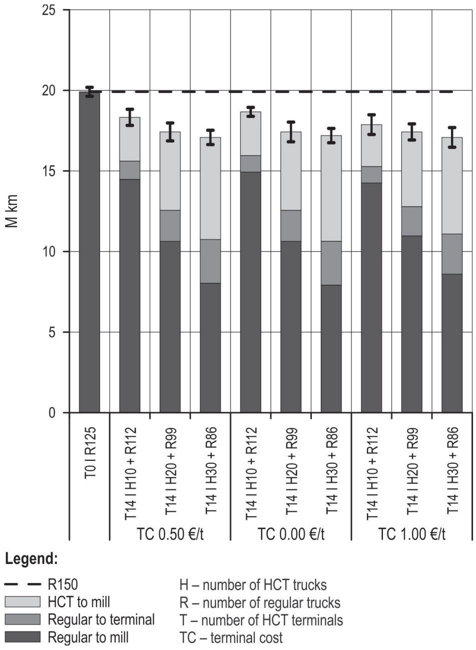


Fig. 6 Transport distances including empty returns according to transport modes in scenarios of 6500 t total transport capacity and 0 or 14 HCT terminals. Error bars represent the range of total transport distances in 8 reproduced simulation runs

the lowest possible number of HCT trucks. Out of the HCT scenarios producing less costs than the corresponding scenario without HCT, the TTC of 6500 t resulted in 2% lower costs than the TTC of 7800 t on average. With a cost level of € 0.50/t, terminal costs represented 1.4% of the total costs with 10 HCT trucks and 2.2% with 20 HCT trucks. With a cost level of € 1.00/t, the proportions were 2.6% and 4.3%, respectively.

The differences in total costs among all scenarios are small, considering the variation of eight reproduced simulation runs per scenario (denoted by error bars in Fig. 7 and 8). The smallest and the greatest records produced within the same scenario differed by ca. 0.6–2.6% from the average of the eight runs. However, none of the records in the most profitable HCT scenarios (i.e. scenarios of 20 HCT trucks and no terminal cost) exceeded the lowest record in the corresponding scenario without HCT (i.e. scenario of 150 or 125 regular trucks).

4.3 Utilization of HCT terminals

Within the most economic scenarios in each terminal cost category (Fig. 7 and 8), the proportion of wood routed through terminals was about 20% when 10 HCT trucks were used, and 34–39% when 20 HCT trucks were used. The change in terminal cost did not considerably influence the total volumes routed through terminals, but it affected terminal-specific volumes to some extent.

Fig. 9 presents the utilization of HCT terminals in scenarios of 10 and 20 HCT trucks. The most used terminals, i.e. 11, 13 and 14, were located near the transit points of abundant wood supply, and because of the attractive location, the terminals were also ranked high in the order of wood offers. The status of these terminals was nearly the same with 10 and 20 HCT trucks in traffic. When the network was condensed to seven terminals, the total throughput of terminals decreased only marginally. The use of terminals 11, 13 and 14 increased by ca. 10%. The use of terminal 6 increased by more than 100%, while the use of terminals remained the same as in the 14-terminal scenarios.

4.4 Sensitivity analysis

The ratio of HCT trucks to regular trucks was the most important factor affecting the total costs in the sensitivity analysis. As the best scenarios included 10 or 20 HCT trucks, they produced about 1.5–2.0% lower total costs than the scenarios of 30 or 40 HCT trucks or the scenarios without HCT. This impact has a strong correlation with the changes in the utilization of HCT trucks. While the utilization of HCT trucks was as high as 91% in the scenario including 10 HCT trucks, the rate dropped below 80% in the scenarios of 30 and 40 HCT trucks. In contrast, the intensified utilization of regular trucks did not improve the economic output of the system in these scenarios.

In the case of 20 HCT trucks, the exclusion of the terminal cost brought significantly greater savings than in the case of 10 HCT trucks. Based on the high utilization rate of the baseline scenario, it is assumable that the capacity of 10 HCT trucks was not enough to benefit from the increased number of more profitable routes via terminals. Fig. 10 presents the proportional impacts of the sensitivity analysis on the total costs and truck utilization rates.

5. Conclusions

The results of the case study indicate that partial replacement of the current pulpwood transport system with HCT would have a significant positive impact on traffic intensity (i.e. decreasing the total number of deliveries) and a small impact on transport economy in the studied area. In this holistic HCT sys-

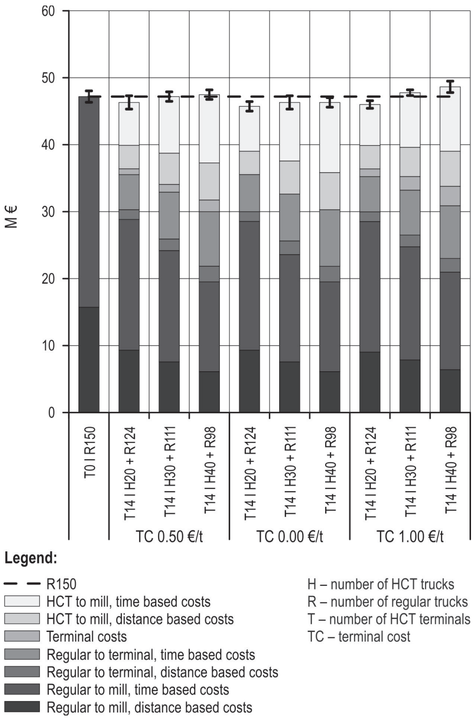


Fig. 7 Transport costs according to transport modes and their cost bases in scenarios of 7800 t total transport capacity and 0 or 14 HCT terminals. Error bars represent the range of total costs in 8 reproduced simulation runs

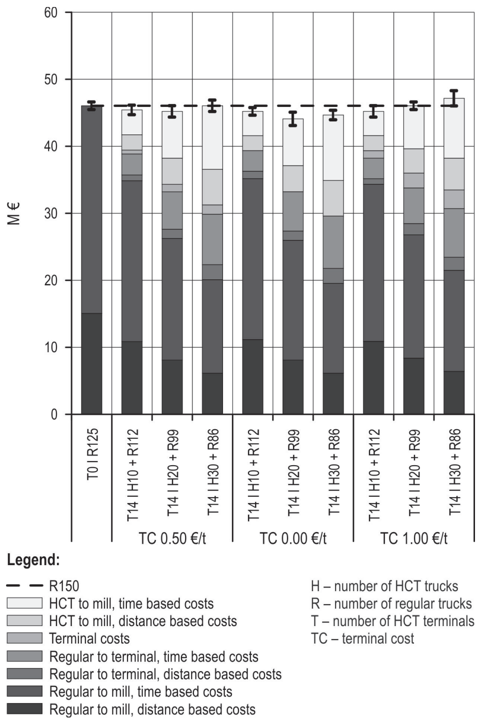
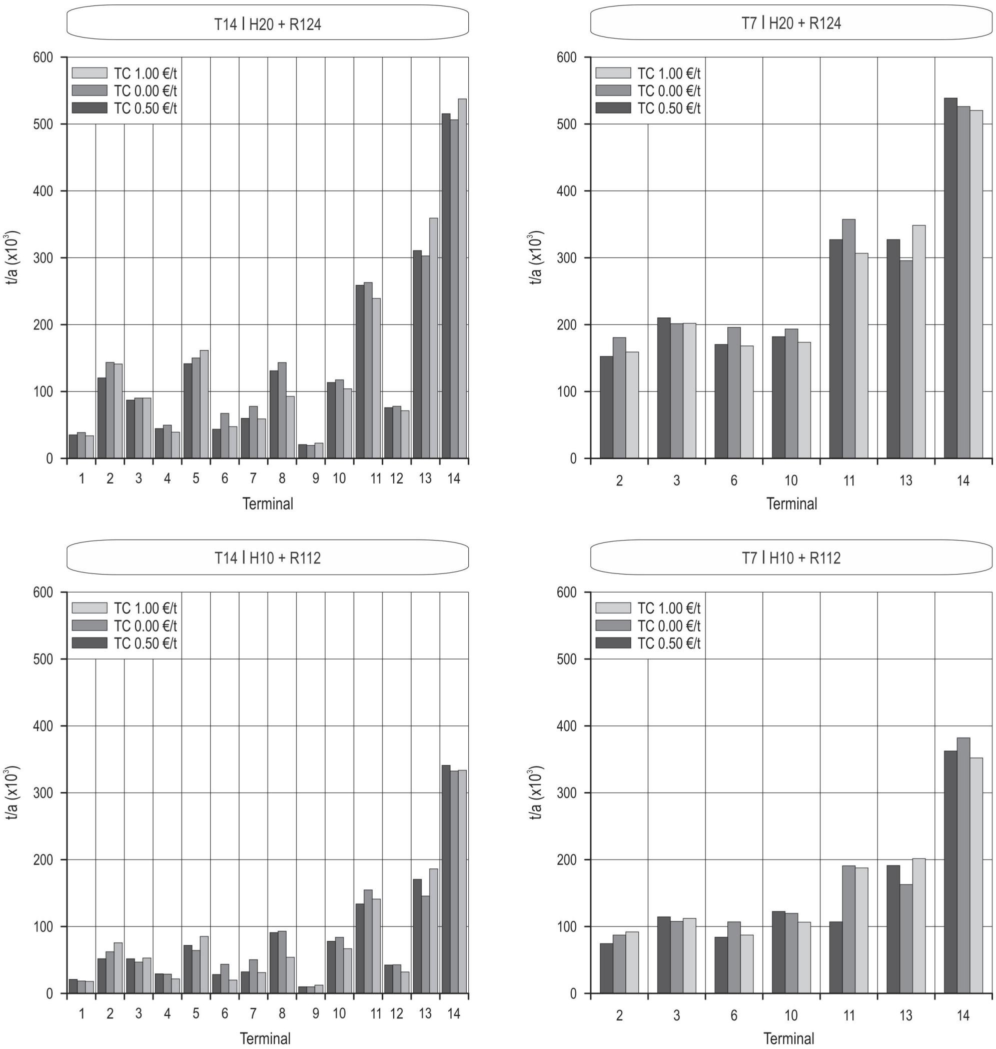


Fig. 8 Transport costs according to transport modes and their cost bases in scenarios of 6500 t total transport capacity and 0 or 14 HCT terminals. Error bars represent the range of total costs in 8 reproduced simulation runs



Legend:

H – number of HCT trucks
R – number of regular trucks
T – number of HCT terminals
TC – terminal cost

Fig. 9 Utilization of HCT terminals in 12 HCT scenarios

tem study, spatial (e.g. bidirectional transport of the same wood stack near terminals), temporal (e.g. additional loading times), and transport-modal (compulsory transshipment) factors together seemed to reduce the economic profitability found in the previous cost analyses of individual trucks or supply chains (e.g.

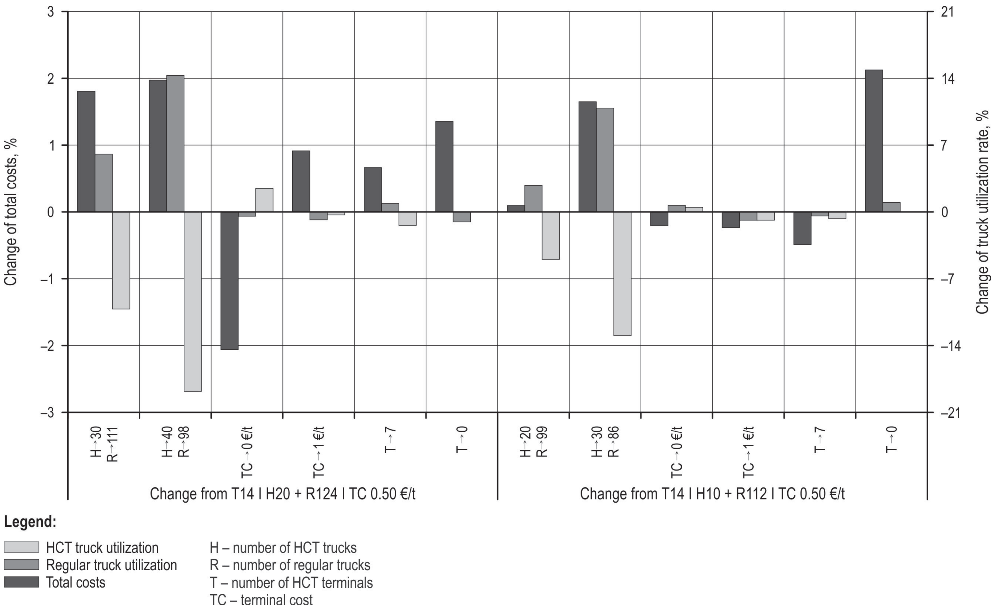


Fig. 10 Impacts of changes in truck number, terminal costs and terminal network on total costs and utilization rates of trucks

Fogdestam and Löfroth 2015, Venäläinen and Korpilahti 2015, Laitila et al. 2016).

The economic performance of HCT is largely dependent on the balance between HCT trucks and regular trucks that feed the HCT terminals. It can be conservatively concluded that a substitution of ca. 10% of the capacity by HCT trucks would cut the total cost by ca. € 1 million (i.e. ca. 2%) in the case. In practice, the transition to the HCT system would happen gradually because there are several transport companies with varying interests in fleet investments. The findings of the case study are promising in this aspect because positive system impacts are achieved already with a relatively small increase in the number of HCT trucks.

The most used HCT routes in the case study were shorter than 100 km, principally because the mills nearest to the HCT terminals were not further away. Extending the studied area would call for more spatial data collection from the neighbouring regions, and most likely, a sparser supply-point grid to keep the runtime performance of the model at a tolerable level. On the other hand, SimPulp could be developed with backhauling options, i.e. a procedure for HCT trucks to find the nearest terminal offering wood so as to minimize the return trip distances with empty loads from the mill for each truck.

Acknowledgements

The work was carried out in the project »Terminal Operations in Energy Efficient Timber Logistics« funded by the European Regional Development Fund. The authors want to give special thanks to Mr Asko Poikela for preparing and validating the cost data of HCT trucks, and to the steering group of the project for advising in the development work and verification of the SimPulp model.

6. References

Almeder, C., Preusser, M., Hartl, R.F., 2009: Simulation and optimization of supply chains: Alternative or complementary approaches. OR Spectrum 31(1): 95–119.

AnyLogic Company, 2017: Defining routes on GIS map.

Asmoarp, V., Enström, J., Bergqvist M., von Hofsten, H., 2018: Effektivare transporter på väg – Slutrapport för projekt ETT 2014–2016. Skogforsk, Arbetsrapport 962, 65 p.

Biswas, S., Narahari, Y., 2004: Object oriented modeling and decision support for supply chains. European Journal of Operational Research 153(3): 704–726.

Carlsson, D., Rönnqvist, M., 2007: Backhauling in forest transportation: models, methods and practical usage. Canadian Journal of Forest Research 37(12): 2612–2623.

ELY Centre Pirkanmaa, 2015: Liite lupapäätökseen Y120 Raskaat yhdistelmät.

Crooks, A.T., Castle, C., 2012: The integration of agent-based modelling and geographical information for geospatial simulation. In: Heppenstall, A.J., Crooks, A.T., See, L.M., Batty, M. (eds.), Agent-based Models of Geographical Systems, Springer, New York, 219–252.

Finnish Customs, 2016: ULJAS – Statistical database.

Finnish Transport Agency, 2015: Digiroad.

Finnish Transport Agency, 2016: Digitraffic.

Finnish Transport Agency, 2017: Statistics on domestic waterborne traffic in Finland 2016. Statistics from the Finnish Transport Agency 2/2017.

Finnish Transport Safety Agency, 2017: HCT-rekat.

Fogdestam, N., Löfroth, C., 2015: ETTdemo 2011–2013: Slutrapport, demonstration av ETT- och ST-fordon. Skogforsk, Arbetsrapport 872, 40 p.

Government decree 407/2013: Valtioneuvoston asetus ajoneuvojen käytöstä tiellä.

Heinonen, T., 2016: High capacity transport – ajoneuvoyhdistelmien vaikutukset liikennevirtaan. Master's Thesis, Aalto University, School of Engineering, 134 p.

Iikkanen, P., Sirkiä, A., 2011: Rataverkon raakapuun terminaali- ja kuormauspaikkaverkon kehittäminen – Kaikki kuljetusmuodot kattava selvitys. Finnish Transport Agency, Transport System. Helsinki 2011. Research reports of the Finnish Transport Agency 31/2011.

Impola, R., Tiihonen, I., 2011: Biopolttoaineterminaalit – Ohjeistus terminaalien perustamiselle ja käytölle. Research report: VTT-R-08634-11, VTT, 38 p.

Jäppinen, E., Korpinen, O.J., Ranta, T., 2013: The effects of local biomass availability and possibilities for truck and train transportation on the greenhouse gas emissions of a small-diameter energy wood supply chain. BioEnergy Research 6(1): 166–177.

Korpinen, O.J., Jäppinen, E., Ranta, T., 2013: Geographical origin-destination model designed for cost-calculations of multimodal forest fuel transportation. Journal of Geographical Information Systems 5: 96–108.

Kühmaier, M., Erber, G., Kanzian, C., Holzleitner, H., Stampfer, K., 2016: Comparison of costs of different terminal layouts for fuel wood storage. Renewable Energy 87: 544–551.

Lahti, O., Tanttu, A., 2016: Report on summertime High Capacity Transport (HCT) 2015. Finnish Transport Safety Agency.

Laitila, J., Asikainen, A., Ranta, T., 2016: Cost analysis of transporting forest chips and forest industry by-products with large truck-trailers in Finland. Biomass and Bioenergy 90: 252–261.

Ministry of Employment and the Economy, 2012: Strategic programme for the forest sector.

Mooney, P., 2015: An outlook for OpenStreetMap. In: Arsanjani, J., Zipf, A., Mooney, P., Helbich, M. (eds.), OpenStreetMap in Geographic Information Science: Experiences, Research, and Applications. Springer International, 319–324.

Natural Resources Institute Finland, 2015a: Forest industries' wood consumption by region 1989–2014 (1000 m^3). Statistics database – Forest statistics – Economy – Forest industries' wood consumption.

Natural Resources Institute Finland, 2015b: Industrial roundwood removals by region. Statistics database – Forest statistics – Structure and production – Industrial roundwood removals by region.

Natural Resources Institute Finland, 2015c: MS-NFI Download Service: MS-NFI products from year 2013.

Natural Resources Institute Finland, 2016: Forest industries' wood consumption 2015. Statistics database – Forest statistics – Economy – Forest industries' wood consumption.

Palander, T., Väätäinen, J., 2005: Impacts of interenterprise collaboration and backhauling on wood procurement in Finland. Scandinavian Journal of Forest Research 20(2): 177–183.

Poikela, A., 2017: Personal communication 2 Oct 2017.

Räsänen, T., 2015: Estimated roundwood supply from municipalities. Unpublished.

Strandström, M., 2016: Timber harvesting and long-distance transportation of roundwood 2015. Metsätehon tuloskalvosarja 4b/2016.

Swedish Road Administration, 2018: BK4 – ny bärighetsklass effektiviserar industrins godstransporter.

Swedish Transport Agency, 2018: Lasta lagligt.

Venäläinen, P., Korpilahti, A., 2015: HCT-ajoneuvoyhdistelmien vaikutus puutavarakuljetusten tehostamisessa – Esiselvity MEE Publications, Corporate 30/2015.

Venäläinen, P., 2017a: Puuyhdistelmien kokojakauma. Unpublished.

Venäläinen, P. (Ed.), 2017b: Terminaalitoiminnot energiatehokkaassa puutavaralogistiikassa – Loppuraportti Metsätehon tuloskalvosarja 4/2017.

Virkkunen, M., Raitila, J., Korpinen, O.J., 2016: Cost analysis of a satellite terminal for forest fuel supply in Finland. Scandinavian Journal of Forest Research 31(2): 175–182.

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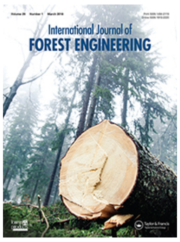
Received: January 10, 2018
Accepted: July 9, 2018

Publication III

Aalto, M., Korpinen, O-J., Ranta. T.
Achieving a Smooth Flow of Fuel Deliveries by Truck to an Urban Biomass Power Plant in Helsinki, Finland – an Agent-Based Simulation Approach

International Journal of Forest Engineering
Vol. 29(1), pp. 21–30, 2018.



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International Journal of Forest Engineering

ISSN: 1494-2119 (Print) 1913-2220 (Online) Journal homepage: http://www.tandfonline.com/loi/tife20

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INTERNATIONAL JOURNAL OF FOREST ENGINEERING, 2018
VOL. 29, NO. 1, 21–30
https://doi.org/10.1080/14942119.2018.1403809

Achieving a smooth flow of fuel deliveries by truck to an urban biomass power plant in Helsinki, Finland – an agent-based simulation approach

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ABSTRACT

Power plants that use biomass for fuel can have heavy truck flow rates, especially during winter. From the viewpoint of power plant operations, it is important that this flow of trucks is smooth; a traffic jam can lead to a decrease in the efficiency of the plant or, at worst, to unwanted shutdowns. To study the effects of different logistics solutions on the truck flow in the reception area of a plant, an agent-based simulation model was created. The model mimics the movement of trucks at a fuel reception site. The case selected for this is a power plant, planned for construction in the Helsinki area of Finland. The model period was set as one month during winter time. The case studies the effects of a second weighing station, automatic sampling and the income flows of different truck types. The results show that a second weighing station alleviates potential problems with the truck flow, compared to only having one weighing station, but a more effective way to improve fuel reception would be to decrease the unloading time by using automatic sampling. It was found more beneficial to use high capacity trucks for fuel reception, as fewer trucks need to enter the plant. The study shows that agent-based modeling can be utilized as a study method in power plant fuel reception areas, where all elements affect each other due to the dynamic nature of the logistics.

ARTICLE HISTORY
Received 26 April 2017
Accepted 8 November 2017

KEYWORDS
Dynamic simulation; agent-based model; logistics; queuing; arrival process; forest chips

Introduction

Woody biomass has, historically, been the most commonly used energy source in Finland (Official Statistics of Finland (OSF) 2016) and future scenarios accounting for Finnish targets in international energy and climate policies indicate that the utilization of wood-based energy sources will continue to grow (Kara 2001). Accordingly, it can be expected that the number of power plants using woody biomass as a fuel will also increase in the future.

Studying the different logistical solutions for the feedstock biomass supply of new plants is reasonable because the supply systems tend to be complex. For example, the systems include multiple feedstock sources, and they are dependent on other systems, such as roundwood or pulp chip transportation. Moreover, climatic factors with significant variation should be taken into account in comprehensive system analyses. With dynamic simulation, a complex system can be studied by building a model to study the effects of multiple factors that interact with the system (Sayama 2015). This method allows for the cost-effective study of various system designs in different scenarios. These studies can be performed on systems that have been built or on systems that are at the design phase, providing new information that static analyses cannot provide about the system.

In Finland, competition for feedstock already appears intense in the most densely populated regions with high energy demand. For example, in Southern Finland, the average supply-demand balance of forest fuels is negative (Anttila et al. 2014), despite the fact that even more biomass plants are under construction or planned (Anttila et al. 2014). In this region, at least three logistical challenges arise: (1) long-distance transportation by rail and waterways should be developed to reach the remote areas of oversupply profitably, (2) the utilization of the existing truck-transport fleet should be maximized to meet the increasing local demand for feedstock, and (3) truck transportation should be scheduled to avoid the commuter traffic rush hours in and near urban areas. This study deals principally with the second challenge, as the flow of trucks in power plant reception areas is an important factor affecting the utilization rate of the fleet (Holzleitner et al. 2011).

Because of the low energy density of biomass, a biomass power plant requires greater volumes of fuel in comparison to plants using fossil fuels, leading to a higher impact on power plant operations and the cost of biomass in terms of logistics (Ranta et al. 2002). In high demand seasons, the truck flow can overflow and choke the fuel reception, leading to a sharp decrease in the efficiency of the plant, or at worst to unwanted shutdowns (Ranta et al. 2002). Studying different logistical solutions in practice is inconvenient because the specific layout depends on the location of the power plant, and construction of the required facilities is expensive. Studying logistics with a simulation approach removes these problems and allows for the testing of the planned logistical solutions before investments are made (Borshchev & Filippov 2004). Due to the complicated nature of a dynamic simulation, the creation of a simulation model requires the

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involvement of an expert with knowledge of the model and the study subject.

Problems with increasing the flow of trucks may arise when a new plant is planned or at an existing plant if the total capacity of the plant is increased, as has been the case at some combined heat and power (CHP) plants (Hakkila 2003). Studies have been carried out into ways of improving fuel reception at power plants by analyzing new technology applicable to reception machinery and new concepts (Impola 2001; Karppinen 2014). These studies could have been improved by including the dynamic element of the logistics, using dynamic simulation. The dynamics of these studies are also subject to change due to the transportation fleet shifting towards higher capacity trucks in Finland (Venäläinen & Korpilahti 2015).

Discrete-event simulation (DES) is a commonly used method in operational research focusing on logistics (Banks et al. 2002; Eriksson 2016), and DES has also been widely used in studies of biomass supply systems (Väätäinen et al. 2005; Mahmoudi et al. 2009; Asikainen 2010; Mobini et al. 2011; Karttunen et al. 2012; Zhang et al. 2012; Zamora-Cristales et al. 2013; Windisch et al. 2015; Eriksson 2016). For example, Mobini et al. (2011) developed a holistic simulation model to analyze the impacts of different supply chain elements on the feasibility of an entire system and the operational reliability of a biomass power plant. Väätäinen et al. (2005) assessed how scheduled arrivals to an existing CHP plant utilizing peat and forest biomass could cut queuing times and improve logistics. Agent-based simulation (ABS) is a relatively novel method in the field, providing more flexibility in the design of a simulation model than DES (Becker et al. 2006). For example, the vehicles in a transportation system can be assigned unique properties, and they can communicate with each other in the system when they are represented by agents in ABS (Becker et al. 2006). The agents in the model are capable of making decisions by themselves, and depending on the current situation, other agents can also be involved in this decision-making process (Borshchev & Filippov 2004; Anylogic 2015). A few studies have found this method to be applicable to biomass supply systems (Karttunen et al. 2013; Jäppinen et al. 2015; Krishnan 2016). A slight disadvantage of ABS is its lower runtime performance compared to that of DES, particularly when the case under study requires the ABS model to contain an enormous number of interacting agents (Becker et al. 2006). This can usually be tackled by improving the design of the model (e.g. changing the level of abstraction) or by increasing the computing capacity, which is nowadays relatively inexpensive. While this study focused only on a subsystem of biomass procurement, i.e. power plant reception facilities, the computing load was not assumed to hinder the use of ABS. Instead, the interactive properties of the ABS method were considered essential in a system where interactions between truck drivers, for example establishing arrangements to enter operation, are common in real life.

The majority of the previous studies utilizing a simulation approach (e.g. Becker et al. 2006; Mahmoudi et al. 2009; Asikainen 2010; Mobini et al. 2011; Karttunen et al. 2012, 2013; Zhang et al. 2012; Zamora-Cristales et al. 2013; Eriksson et al. 2014; Jäppinen et al. 2015; Windisch et al. 2015; Eriksson 2016; Krishnan 2016) focus on the whole supply system, presenting the plant reception facilities as a generalized element within the system. In this study, the reception area of the plant was described more precisely, assigning individual properties to the elements inside the plant yard. The purpose of this was to evaluate how different time consumption parameters at a biomass feedstock reception site affect the performance of the fuel delivery system and to discuss the impact of the properties of the truck fleet on performance. The case studied is a biomass power plant at the design stage in the Helsinki metropolitan area, Finland (2016, Personal communication, Helen Ltd.). In comparison to studies focusing on existing power plants, the research framework of this study is different, as there are usually several ways of realizing the layout of reception facilities (e.g. defining the locations of permanent buildings and the number of measurement and unloading points) in an unbuilt environment. As the plant and its fuel reception area are at the planning phase and the transportation fleet properties may change in the future (Venäläinen & Korpilahti 2015), different scenarios, including the present and the possible future transportation fleet properties, are also studied in this paper.

Materials and methods

Case studied

The case area is a power plant yard that an energy company, Helen Oy, is planning to construct in Helsinki (N 60°13′ 24′′, E 25° 9′ 47′′) (2016, Personal communication, Helen Ltd.). The plan includes a boiler with a 250 MW fuel capacity and two 18,000 m^3_{loose} fuel storage facilities at the site. The plan also has a reservation for two weighing stations and four drive-through bays in the unloading building. Next to the unloading building is an area in which trucks can wait their turn to unload, if all unloading bays are in use. This waiting area has capacity for five trucks.

The total project area is 5.8 ha, of which 0.8 ha would be occupied by permanent buildings. The remaining 5 ha space is assumed to be available for truck traffic, with a 0.2 ha area dedicated to covered conveyor bridges on which trucks are forbidden to stop. The total distance that the trucks travel at the plant is estimated to be 665 meters. The planned layout of the plant yard is show in Figure 1.

According to the plans, trucks will arrive in the fuel reception area through the northern gate and continue to the weighing station. From there, the trucks will go on to an unloading building on the west side. The trucks will drive through the unloading building and return to the weighing station, after which they will leave through the same gate that they arrived from. Based on the plans, the trucks will use the same weighing bridge both on arrival and departure. This design eases the calibration of the weighing bridges but forces the trucks to go to the same location for weighing. The movements, including the estimated distances and the average speed of the trucks, are presented in Table 1.

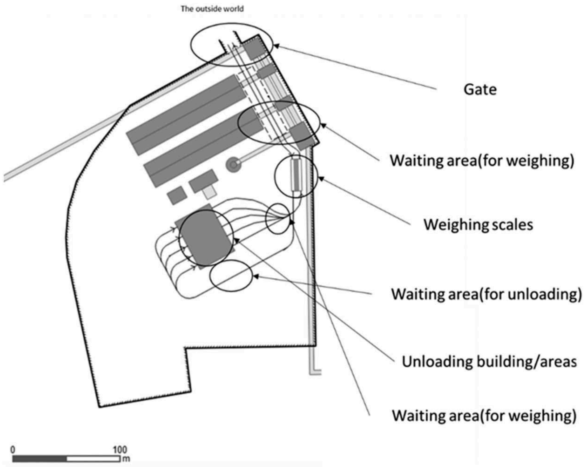

Figure 1. The layout of the planned fuel reception yard.

Table 1. Distances and average speeds of the layout.

Routing features	Distance [m]	Speed [km/h]
Gate ≫ Waiting (for weighing)	100	10
Waiting area ≫ Weighing scales 1	40	5
Waiting area ≫ Weighing scales 2	40	5
Weighing scales 1 ≫ Waiting (for unloading)	130	10
Weighing scales 2 ≫ Waiting (for unloading)	130	10
Waiting area ≫ Unloading point 1	130	10
Waiting area ≫ Unloading point 2	130	10
Unloading point 1 ≫ Waiting (for weighing)	85	5
Unloading point 2 ≫ Waiting (for weighing)	85	5
Waiting area ≫ Weighing scales 1	40	5
Waiting area ≫ Weighing scales 2	40	5
Weighing scales 1 ≫ Gate	140	10
Weighing scales 2 ≫ Gate	140	10

The sampling of the fuel is carried out either by the truck driver after unloading the cargo or by an automatic system that take samples from moving fuel stream (SFS-EN 2011a). Automatic systems require their own operation systems, which increase the initial costs of the plant reception area, but they decrease the running costs by speeding up the vehicle flow (SFS-EN 2011a). The effect of the automatic sampling is studied by adjusting the unloading time. If sampling is manual, it is assumed that the driver will take samples of the fuel by following the instructions given in standard SFS-EN 14,778 (SFS-EN 2011a) and prepare the sample in accordance with the instructions given in standard SFS-EN 14,780 (SFS-EN 2011b). The time required to take a sample is estimated to be 10 min.

Description of the model

The simulation model was created with the Anylogic™ simulation software as an agent-based model, and the description follows the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models (Grimm et al. 2006, 2010).

Purpose

The model allows for the study of the effects that different power plant yard layouts have on the flow of vehicles in a fuel reception area. The model simulates the movement and operations of the vehicles at the power plant. The characteristics of the operations can be set by the model user and the location where these operations will take place can be adjusted via the dynamic layout. With these settings, the user can study how the flow of vehicles behaves with different plant demand loads.

Entities, state variables and scales

The fuel reception model focuses on the movement of vehicles. The agent associated with a vehicle is called a truck agent. Truck agents move inside the main agent, which also hosts storage and weighing station agents. The model also has fuel entity agents, which each represent one cubic meter of loose fuel. A number of these can be carried by the truck agent, based on values set by the user.

The type parameter determines the vehicle type, which in turn determines the capacity parameter, the presentation of the agent and the effects on logical decisions, which are made during fuel delivery.

The truck agents move within a network that consists of points and paths. Different operations take place at these points. The weighing station agent is located at one point, and the user can determine whether one or two weighing stations are used, with these agents having their own points. There are also points for waiting before operations and unloading. There are two unloading points, in which any number of bays may be located. In each bay only one truck agent can be unloaded at a time.

Truck agents interact with the agents at points in the network and with each other to select the best locations to go to and to determine which queuing point an agent belongs to. Truck agents cannot overtake other truck agents by driving past them, but faster unloading may change the order of the agents. In order to prevent confusion, all truck agents are assigned their own ID number.

The network within which the trucks move is shown in Figure 2. The distance to the next point and the travel time are shown next to the path. These values create the layout of the fuel reception area. The model presentation does not scale to the values the user sets. The speed of truck agents is determined for every path by these values.

The storage agent cannot be seen within the network, as it does not have a visual presentation and its location does not affect the logic of the models. This is based on the assumption that the fuel is transported from the unloading area to the storage facility by conveyors. The storage facility has a capacity that determines how many fuel entity agents it can hold. At the storage agent there is a sink that destroys fuel entity agents based on the utilization rate and the fuel power of the plant.

Process overview and scheduling

Truck agents are created at frequencies predefined by the user. The truck agent receives information about its vehicle type when created, using the setType function, which sets the proportions that the user has assigned with random number generator.

After the truck agent receives its vehicle type information, it sets its properties based on its vehicle type. These properties include capacity, unloading time and visual presentation. After its creation, the truck agent calls the amount of fuel entity agents it can hold based on its capacity, and picks them up. When loaded, the truck agent enters the network and starts to move from point to point. Truck agents' movements can be followed on the visual representation as colored circles. There is a limit to how many truck agents can be present in some parts of the network.

After entering the plant, the truck agent moves to a waiting area prior to weighing, if there is room for an agent. The waiting area for weighing is located inside the weighing station agent and the truck agents choose the weighing station agent with fewest truck agents inside. The truck agent will remember the weighing station agent it visited during arrival, as it will need to visit the same weighing station agent when leaving. The truck will move to the weighing bridge when it becomes free, and there can only be one vehicle in the weighing bridge area at a time.

After the weighing station, the truck agent moves on to wait for an unloading bay to become free. The truck agent will enter the unloading area if there is a suitable bay available for it. In the unloading area, fuel entity agents are removed from the truck agent, which will be delayed based on the unloading speed and the capacity of the agent.

After unloading, the truck goes to the same weighing station agent it visited at arrival. The weighing process is the same as on arrival. Afterwards, the truck agent leaves the network and is destroyed. A simplified visual presentation of the process from the point of view of the truck is shown in Figure 3.

Design concepts

The main purpose of the model is to gain a better understanding of how power plant truck traffic behaves during high traffic periods. The design is straightforward and includes the following steps:

- Simulating operations that the truck goes through during the reception of fuel
- Creating a path for the trucks and measuring trucks performance
- Fulfill plant demand by arriving trucks.

The main assumptions and boundaries of the model are:

- Only time and operations inside the yard are taken account
- All trucks are fully loaded and fuel quality is constant
- All trucks' speeds are equal and their turning radii do not limit movements
- All of the drivers perform at the same level, meaning that delays are vehicle type specific
- There is no human or other movement in the yard hindering truck movements.

The arrival of truck agents can be distributed exponentially by a random number generator. Exponential distribution is frequently used to represent randomly occurring events (Anylogic 2015). Due to the stochasticity, it is possibile that the daily number of trucks arriving will diverge from the value set by the user. The problem of having too few truck agents arriving is resolved by multiplying the arrival rate by 1.2, directing arrivals more start of the shift. This leads to having too many trucks arriving, which can be solved by having a counter that counts the number of trucks arriving and setting the rate to zero when a predetermined number of daily arrivals is reached. If a truck has already been inserted into the model, it will finish its delivery even if the work shift has ended.

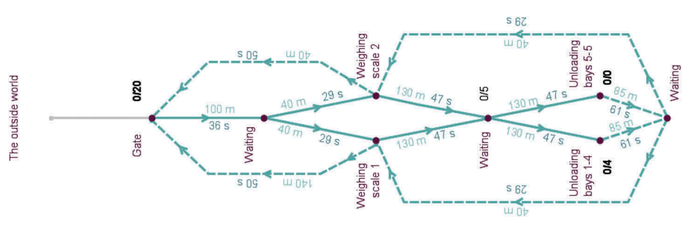

Figure 2. The layout of the fuel reception yard in the model.

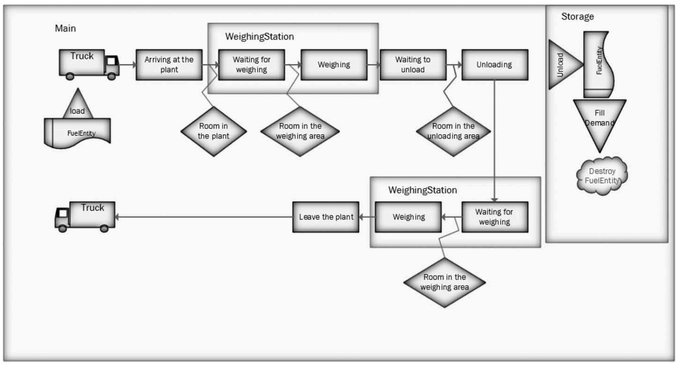

Figure 3. Simplified presentation of the model process. The rectangles are actions performed by the truck agent and the diamonds are statements for moving to the next phase. Transparent rectangles represent the agent boundaries, and the triangles show the movements of the fuel entity agent.

The model records the times at which truck agents arrive at locations and how long it takes for the truck agents to perform each operation. These values are saved to the dataset and when the model has finished running, this dataset is exported to a spreadsheet. In addition, the number of trucks in the waiting locations is recorded and exported. To see if the desired amount of fuel is arriving, the storage situation is recorded and this data is also exported to a spreadsheet.

Initialization

Before starting to run the model, the user sets the initial values in a spreadsheet. These values are imported at the start of the model. Before the model is started, the user selects how many weighing stations and what work shift are to be used in the simulation via the model window.

Based on the imported initial values, the storage agent creates fuel entity agents to fill the storage facilities to the initial level, and the model starts running. The start time is set to 0:00:00 on 1 January 2015 and the end time is set to 0:00:00 on 30 January 2015. The model's time unit is set to minutes and the fixed time step is 0.001 minutes.

Input data

As previously mentioned, the input data is imported from a spreadsheet, in which the user can set values for the plant and the reception area. These values include the number of truck agents allowed in different areas, the monthly fuel usage of the power plant – based on fuel power and utilization, the distances and the speed that the truck agents drive at along paths in the network, and how many trucks arrive daily.

The tables in which the arrival rates of the vehicles are set show the hourly arrival rate for each work shift. They also include a monthly estimation of the supply and demand of the power plant to help the user to set the balance scenario in the model.

Table 2 presents the input values for yard properties. These include the storage capacity, the number of unloading bays in different areas, the number of trucks allowed in different areas, and properties of the paths within the network. The average speed of a truck agent for each path can be set and this value should take account of the accelerating and decelerating of the truck agent.

Table 2. Input table for yard properties and measuring and reception properties.

Yard properties		Measuring and reception	
Storage capacity of the plant, m^3	18,000	Weighing time (in), min	3
Number of storage silos	2	Weighing time (out), min	3
Initial filling degree for each silo	50%	Bays at unloading point 1	4
Max. vehicles in waiting area before weighing	5	Bays at unloading point 2	0
Max. vehicle count allowed at plant	20		
Max. vehicles in waiting area before unloading	5		

Submodels

To make sure that stochasticity does not play too big a role, a sensitivity analysis experiment was added to the model. This experiment runs the model eight times and records the results for each run. In sensitivity analysis mode, a visual presentation of the simulation run is not available.

Model set-up for the case studied

The model is set to correspond to the current case by defining the input values in the input file. The work shift used for this study has trucks arriving at the reception from 6 am to 10 pm every day. A 3-minute weighing time was estimated for the simulation, using the parameters reported by Ranta et al. (2014). This includes the truck driver walking to a monitor and inputting information about the delivery. The weighing station can measure the weight of the truck and the trailer at the same time. For incoming trucks, there are four spots in which to wait for their turn at the weighing station. The capacity of the waiting area for departing trucks is unlimited.

The four planned unloading bays in the fuel reception area are included in the model. These bays are assumed to be identical and located in unloading point 1. The conveyor that moves the fuel from the bay to the storage facility is assumed to be scaled to prevent a bottleneck situation with the incoming fuel flow. The time that the unloading takes depends on the unloading method and the configuration of the unloading area. Different methods for unloading include side tipping, back tipping, and moving floor set-ups (Angus-Hankin et al. 1995). Depending on the unloading area, the trailer and the tractor can be unloaded without being detached. Some unloading areas require the truck to be reversed into the area. In this design, it is assumed that the trucks can drive through the unloading area and the full trailer trucks can be unloaded without the need to detach the trailer.

The unloading rate of 310 m^3_{loose}/h that was used in the simulation, with 17.3% variation, was determined using studies by Väätäinen et. al. (2005) and Ranta et. al. (2014). In Väätäinen et. al. (2005), an unloading rate of 300 m^3_{loose}/h was used for the rear unloading trucks, and Ranta et. al. (2014) concluded an average unloading rate of 310 m^3_{loose}/h with a 54 m^3_{loose}/h standard deviation.

At the beginning of each simulation run, the storage facilities is assumed to be half-filled, in order to avoid emptying or overfilling of the storage facilities during the simulation run.

The simulation period used in the model was January, and the plant was therefore assumed to be running at full capacity. This means that the plant uses 6000 MWh of fuel per day and 180 GWh of fuel in 30 days. The fuel that the plant is designed to use is woody biomass with a moisture content of 30–40%. Based on these properties, the energy density of the fuel was set to be 0.8 MWh/m^3_{loose} (Alakangas et al. 2016).

The model includes a visualization of the simulation. Figure 4 shows the process of converting the plant layout draft to the model visualization. In the visualized output it is possible to verify that the truck movements and functions are working as designed. Debugging is used to ensure that the parameters impact the correct variables. Debugging runs are carried out with simple setups, e.g. only one truck inside the model, to simplify the process of finding incorrect parameters or faulty logic in the model. The model was developed and usage carried out with input from an expert in the field to ensure model functions.

The features focused on are automatic sampling and the number of weighing stations. The effect of the automatic sampling is studied based on the unloading time. Automatic sampling is assumed to have no effect on the operation of trucks and will not add any delay to the unloading. If the sampling is carried out by the driver, it is assumed that it will take 10 min. During manual sampling, the plant has only one weighing station.

The effect of the second weighing station is studied by first running the model with only one weighing station, and then repeating the run with two weighing stations. The time required for weighing is assumed to be the same at both weighing bridges. The sampling is assumed to be automatic when studying the effect of the weighing station. The time that the trucks spend at the site and in waiting areas is recorded and the effect of the different set-ups evaluated.

Transport fleet

Biomass comminution was assumed to be prohibited in the plant yard and, therefore, all arriving trucks were the same kind of chip trucks with fixed containers, as presented in Figure 5. Four different truck types were included in the model, and they were classified according to their volumetric capacity. Truck type classification was based on three scenarios for the development of a truck fleet for comminuted biomass transportation in Finland. Scenario 1 represented the current situation in terms of real-world truck type distribution, based on a survey conducted by Venäläinen and Poikela (2016), and Scenario 2 represented the ongoing shift towards higher transport capacity trucks (Venäläinen & Poikela 2016). Scenario 3 includes high capacity transportation (HCT) trucks with a capacity of 180 m^3_{loose}. This scenario was used as it can result in a 10% cost saving compared to scenario 1 (Venäläinen & Poikela 2016). There are HCT trucks currently under demonstration on the Finnish road

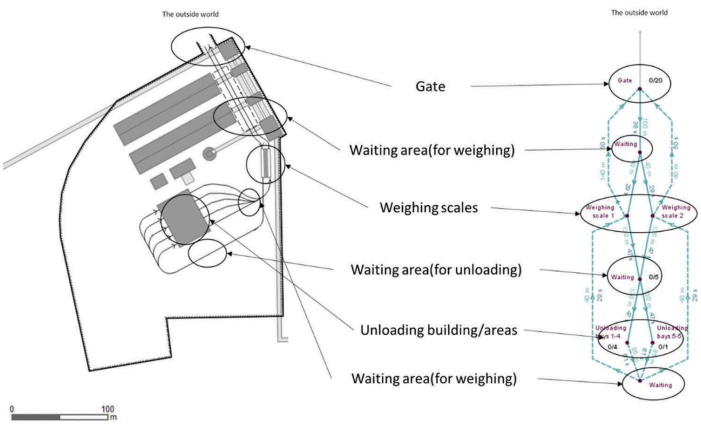

Figure 4. The layout of the planned fuel reception yard and its corresponding representation in the simulation model.

Figure 5. Container of the type used in the model.

network with temporary operating permits (Venäläinen & Korpilahti 2015). The maximum permitted total weight of a HCT vehicle is 104 tonnes (Venäläinen & Korpilahti 2015).

With the capacities and truck type proportions selected, the fuel supply will not meet the demand exactly, and conditions whereby supply is greater than demand will lead to a surplus of fuel. The surplus was minimized, leading to scenario 1 having a calculated surplus of ~2000 m^3_{loose}. The calculated surplus for scenario 2 and scenario 3 was ~3000 $m^3_{loose.}$ Truck capacities and their proportions of the number of arrivals in each scenario are shown in Table 3.

Due to the stochastic nature of the trucks' arrivals and type selection, the exact number of daily arrivals of different types is not constant. The effect of this is studied though sensitivity analyses by setting sampling to automatic and having only one weighing station.

Table 3. Trucks capacities and their proportions of the number of arrival in different scenarios.

		Scenario 1	Scenario 2	Scenario 3
	Capacity [l-m^3]	Proportion [%]	Proportion [%]	Proportion [%]
Type 1	140	49	40	10
Type 2	145	31	35	35
Type 3	150	20	25	35
Type 4	180	0	0	20
Total number of trucks	-	53	52	48

Results

A sensitivity analysis shows that distribution of the vehicle types arriving differs from the set value. There was a unit difference of approximately 2% between runs. It is important that this stochastic result remains the same as in the input file. Due to this, the results were rejected if the proportions diverged from the input values by more than 1% unit.

The set distribution of the vehicles arriving led to vehicles arriving randomly between 6 am and 10 pm. With all scenarios, the average daily arrival density of the trucks was between three and four trucks per hour from 6 am to 5 pm. After 5 pm the number of trucks arriving decreased gradually, until it reached 0 after 10 pm. The distribution of the trucks arriving was as intended and stochastically acceptable.

The number of arrivals per vehicle type, the sum and the average time that trucks spent at the plant, and the sum of trucks waiting to unload for the results considered acceptable for all scenarios and different facility set-ups are shown in Table 4.

The difference in the total number of truck arrivals between scenarios is due to the capacity of the trucks. Scenario 3 has 150 trucks fewer than scenario 1 and 120 trucks fewer than scenario 2. A lower number of trucks affects the total unloading time. Even when the unloading time per truck is set higher in scenario 3, due to the trucks' larger capacity, the sum of total unloading times for 30 days is shorter, due to the lower number of trucks. With manual sampling, the sum of total unloading times for scenario 3 is 49 hours less than scenario 1 and 35 hours less than scenario 2. With automatic sampling, the effect is less drastic, but the sum of total unloading times in scenario 3 is still over 24 hours less than scenario 1 and over 13 hours less than scenario 2.

Longer unloading times led to trucks remaining in unloading bays for longer, which then affected the waiting times, as can be seen in Figure 6. With manual sampling, where the unloading time was higher, all waiting times were higher. The higher capacity of the trucks and a second weighing station alleviated this problem but in this case the truck flow is still the worst by some way. With automatic sampling, the maximum waiting time before unloading was around 30 min, and with manual sampling, it increased to almost 1 hour in all scenarios.

For all the scenarios with automatic sampling, having two weighing stations decreased all waiting times at the weighing

Table 4. Results for all scenarios and different facility set-ups.

	Trucks arrivals							
	Type 1	Type 2	Type 3	Type 4	Total	Sum of total time at the plant [h]	Average time�� at the plant [min]	Sum of time spent waiting to unload [h]
S1, 1-W, AS	783	497	310	0	1590	1118.4	42.2	25.7
S1, 2-W, AS	770	495	325	0	1590	1080.3	40.8	37.1
S1, 1-W, MS	792	488	310	0	1590	1455.7	54.9	103.6
S2, 1-W, AS	614	543	403	0	1560	1084.8	41.7	16.1
S2, 2-W, AS	626	537	397	0	1560	1054.6	40.6	26.1
S2, 1-W, MS	622	552	386	0	1560	1400.1	53.9	76.5
S3, 1-W, AS	139	497	517	287	1440	1046.0	43.6	21.7
S3, 2-W, AS	146	506	503	285	1440	1004.8	41.9	18.6
S3, 1-W, MS	131	498	515	296	1440	1334.2	55.6	64.7

S, Truck proportion scenario; 1-W, one weigh station; 2-W, two weigh stations; AS, automatic sampling; MS, manual sampling.

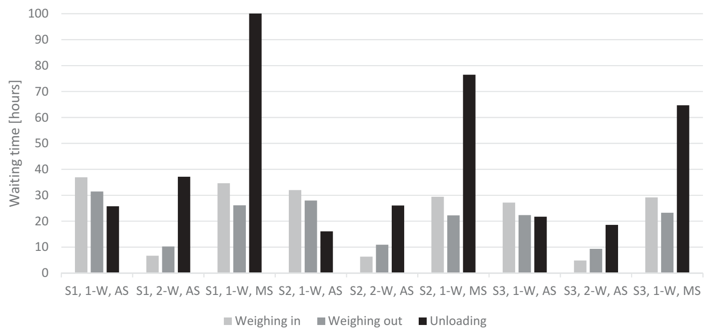

Figure 6. The total time that trucks spent in different waiting areas. S, Truck proportion scenario; 1-W, one weighing station; 2-W, two weighing stations; AS, automatic sampling; MS, manual sampling.

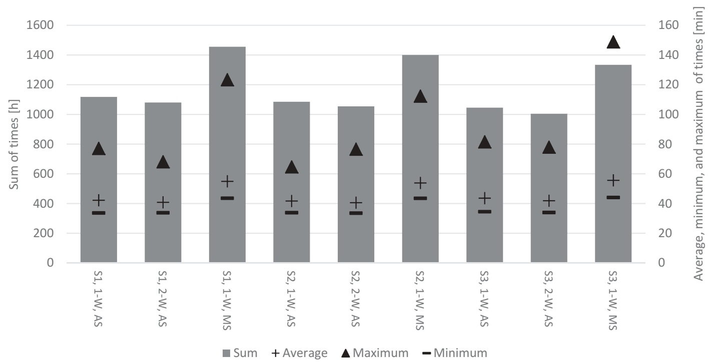

Figure 7. Total time that trucks spent at the plant. The sum of the total times is presented in hours (left axis). The average, minimum, and maximum are presented in minutes (right axis). S, Truck proportion scenario; 1-W, one weighing station; 2-W, two weighing stations; AS, automatic sampling; MS, manual sampling.

station, but in scenarios 1 and 2 there was an increase in the waiting times for unloading. The effect was small, but overall for the 30 days that the trucks were at the plant, a second weighing station saved over 30 hours in every scenario. A second weighing station lowered the average time spent at the site by over one minute per truck when automatic sampling was used.

The average waiting time for weighing on arrival was over a minute with one weighing station. With two weighing stations, this decreased to 15 seconds. The same effect was noticed for outgoing trucks but the difference was not so dramatic. With one weighing station, the average waiting time was around 1 minute and with two around 25 seconds.

The sum of the total times that trucks spend at the plant is presented in Figure 7 with average, minimum, and maximum times. With manual sampling, the total time that the trucks spent at the site was over 300 hours more than with automatic sampling. This is much more noticeable in terms of truck flow and several instances can be seen where all spaces in the unloading waiting area were filled. The waiting area was fully occupied 15 times in scenario 1 and three times in scenarios 2 and 3.

Discussion

Automatic sampling is usually used in the power plant reception area and the simulation results indicate that the 10-min increase that manual sampling adds to the unloading time harms truck flow significantly. This indicates that planning the unloading areas to ensure faster unloading times is a step worth taking. In this study, a 10-min time increase was used to represent sampling time, however, the unloading time can be decreased by designing unloading areas to be easily accessible (e.g. drive through concept, having gradual turns) and ensuring unloading devices have higher unloading rates. One way to increase unloading capacity is increasing the number of the unloading bays or modifying the layout of the yard. Studies using discrete-event simulation have shown the possibility to increase unload capacity at sugarcane mill by introducing new setting at the yard (Iannoni & Morabito 2006; Bocanegra-Herrera & Vidal 2016). Having greater unloading capacity moves the stress to the weighing station. In this study, a second weighing station only alleviates truck flow issues to a minor extent, but this could become more significant if unloading capacity were higher.

In scenarios with higher capacity trucks, the total time at the plant is decreased. This indicates that it is better to have fewer trucks spending a higher amount of time at the plant. A study analyzing HCT at intermodal road-rail transport reports that high-capacity trucks bring cost-savings by improving efficiency (Ye et al. 2014). The higher efficiency of HCT was also found in this case study. At weighing and sampling bigger amount of the fuel was processed in one measurement, consuming same amount of time than other truck types.

In this study, truck arrivals were set to be stochastic, and in a study by Väätäinen et. al. (2005) it was concluded that scheduling the arrivals of the trucks is a very effective way to reduce queuing times. However, this is not always possible for power plants, due to high fuel requirements and levels of traffic in urban areas. One way to make truck arrivals more scheduled is to have a storage yard near the power plant, i.e. a feed-in terminal (Virkkunen et al. 2015).

This study focused on improving the utilization rate of the truck fleet by studying logistical challenges in power plant reception areas. To intensify the usage of existing truck transport, more studies need to be undertaken to research ways to optimize truck flow at supply points and other points in the chain where there is a high density of transport vehicles. Other transport types (e.g. train) may be used to alleviate the density of trucks across the supply chain, leading to less truck-based congestion on roads and at supply and demand sites (Mahmudi & Flynn 2006).

The results of this study indicate that the flow of trucks in power plant yards can be made smoother by adding a second weighing station or implementing automatic sampling, but this study did not take account of the investment costs required to achieve this. These costs should be compared to the benefits of having trucks spend less time in the plant yard. It is worth noting that the model as it is does not take into account fuel quality changes, which are important during value chain optimization (Shabani et al. 2013). These shortcomings of the model could be considered in future models. Other possible research subjects that should be taken into account in future models and studies include the effect of having a terminal close by, options for other forms of transportation, and what is utilization of used machinery.

This agent-based model shows how the dynamic nature of the fuel supply affects plant reception areas. A delay in one place has a knock-on effect, possibly leading to major delays in the supply of fuel. The model was specifically designed for this study case, but it could also be used for other reception concepts. This study focused on maximum fuel consumption over a 30-day period, to see how high traffic in reception areas affects plant yard logistics, but the model has the capacity to be adapted to study annual fuel stock changes, the effect of a malfunction at unloading, different layout concepts and many other problems. All the analyses can be carried out on fuel reception areas at the design phase or for existing fuel reception areas. It can be concluded that agent-based modelling can be broadly utilized for studies of fuel reception areas at power plants.

In conclusion, this study shows that fuel reception area operations alone only cause small delays for individual deliveries, but when scaled up to dozens of deliveries this may disrupt the logistics of the fuel reception area. The truck flow can be eased by adding a second weighing station, but a more effective way is to speed up the unloading procedure. This study demonstrates that agent-based modelling can be utilized as a study method in fuel reception areas where all elements affect each other due to the dynamic nature of the logistics.

Acknowledgements

This study was carried out within the framework of the “Sustainable Bioenergy Solutions for Tomorrow (BEST)” research program. BEST is coordinated by CLIC Innovation Ltd, with funding from the Finnish Funding Agency for Innovation, Tekes. The authors would like to thank Ms Tea Erätuuli and Ms Cecilia Salin from Helen Ltd for giving information of the planned power plant, Mr Matti Virkkunen and Mr Jyrki Raitila from VTT Technical Research Centre of Finland for assisting in time consumption parameters, and Ms Pirjo Venäläinen from Metsäteho Ltd for truck type distribution survey.

Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Alakangas E, Hurskainen M, Laatikainen-Luntama J, Korhonen J. 2016. Suomessa käytettävien polttoaineiden ominaisuuksia [Characteristics of fuels used in Finland]. Finnish: VTT Technical Research Centre of Finland Ltd; p. 258.

Angus-Hankin C, Stokes B, Twaddle A. 1995. The transportation of fuelwood from forest to facility. Biomass Bioenergy. 9:191–203.

Anttila P, Nivala M, Laitila J, Flyktman M, Salminen O, Nivala J. 2014. Metsähakkeen alueellinen korjuupotentiaali ja käyttö vuonna 2020 [Regional harvesting potential and use of forest chips in 2020]. Finnish: Finnish Forest Research Institute; p. 313.

Anylogic. 2015. Anylogic simulation software manual. St. Petersburg: Anylogic.

Asikainen A. 2010. Simulation of stump crushing and truck transport of chips. Scand J For Res. 25:245–250.

Banks J, Jain S, Buckley S, Lendermann P, Manivannan M. 2002. Panel session: opportunities for simulation in supply chain management. Proceedings of the 2002 Winter Simulation Conference; Dec 8–11. San Diego (CA): IEEE, pp. 1652–1658.

Becker M, Wenning B-L, Görg C, Gehrke JD, Lorenz M, Herzog O. 2006. Agent-based and discrete event simulation of autonomous logistic processes. In Borutzky W, Orsoni A, Zobel R, editors. ECMS 2006, Proceedings of the 20th European Conference on Modelling and Simulation; May 28–31. Sankt Augustin: ECMS. pp. 566–571.

Bocanegra-Herrera C C, Vidal CJ. 2016. Development of a simulation model as a decision support system for sugarcane supply. DYNA. 83 (198):180–186.

Borshchev A, Filippov A. 2004. From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. Proceedings of the 22nd International Conference of the System Dynamics Society; Jul 25–29; Oxford, England.

Eriksson A, Eliason L, Jirjis R. 2014. Simulation-based evaluation of supply chains for stump fuel. Int J For Eng. 25:23–36.

Eriksson A. 2016. Improving the efficiency of forest fuel supply chains. Uppsala: Swedish University of Agricultural Sciences.

Grimm V, Berger U, Bastiansen F, Eliassen S, Ginot V, Giske J, Goss-Custard J, Grand T, Heinz SK, Huse G, et al. 2006. A standard protocol for describing individual-based and agent-based models. Ecol Modell. 198:115–126.

Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF. 2010. The ODD protocol: A review and first update. Ecol Modell. 221:2760–2768.

Hakkila P. 2003. Developing technology for large-scale production of forest chips. Wood Energy Technology Programme 1999-2003. Interim report (No. TEKES/TO-RAP–5/2003). Helsinki: Technology Development Centre TEKES.

Holzleitner F, Kanzian C, Stampfer K. 2011. Analyzing time and fuel consumption in road transport of round wood with an onboard fleet manager. Eur J For Res. 130:293–301.

Iannoni A P, Morabito R. 2006. A discrete simulation analysis of a logistics supply system. Transp Res Part E Logist Transp Rev. 42 (3):191–210.

Impola R. 2001. Puupolttoaineille soveltuvat vastaanotto- ja käsittelyjärjestelmät. [Receiving and handling systems suited for wood fuels.] In: Alakangas E, editor. VTT Symposium 216. The Yearbook 2001 of the Finnish Wood Energy Technology Programme; Sep 5–6; Jyväskylä. Espoo: VTT Technical Research Centre of Finland Ltd. p. 315–327. Finnish.

Jäppinen E, Korpinen O-J, Ranta T. 2015. Simulation modelling in biomass logistics-benefits, challenges and three case studies. In: Proceedings of the 23rd European Biomass Conference and Exhibition; Jun 1–4; Vienna: ETA-Florence Renewable Energies; p. 247–250.

Kara M. 2001. Energy visions 2030 for Finland. Helsinki: Edita; VTT Energy 2001.

Karppinen M. 2014. Polttoaineen vastaanotto ja sen kehittäminen – pursialan voimalaitos [Fuel reception and its development – Pursiala Power Plant] [Bachelor thesis]. Lappeenranta: Saimaa University of Applied Sciences.

Karttunen K, Lättilä L, Korpinen O-J, Ranta T. 2013. Cost-efficiency of intermodal container supply chain for forest chips. Silva Fenn. 47:24.

Karttunen K, Väätäinen K, Asikainen A, Ranta T. 2012. The operational efficiency of waterway transport of forest chips on Finland's Lake Saimaa. Silva Fenn. 46:395–413.

Krishnan BR. 2016. Biomass residues for power generation: a simulation study of their usage at Liberia's plantations Master thesis. Ann Arbor (MI): University of Michigan.

Mahmoudi M, Sowlati T, Sokhansanj S. 2009. Logistics of supplying biomass from a mountain pine beetle-infested forest to a power plant in British Columbia. Scand J For Res. 24:76–86.

Mahmudi H, Flynn PC. 2006. Rail vs truck transport of biomass. Appl Biochem Biotechnol. 129(1–3):88–103.

Mobini M, Sowlati T, Sokhansanj S. 2011. Forest biomass supply logistics for a power plant using the discrete-event simulation approach. Appl Energy. 88:1241–1250.

[OSF] Official Statistics of Finland. 2016. Energy supply and consumption. Statistics Finland. [accessed 2016 Aug 22]. http://www.stat.fi/til/ehk/index_en.html.

Ranta T, Föhr J, Karttunen K, Knutas A. 2014. Radio frequency identification and composite container technology demonstration for transporting logistics of wood biomass. J Renew Sustain Energy. 6:013115.

Ranta T, Halonen P, Frilander P, Asikainen A, Lehikoinen M, Väätäinen K. 2002. Metsähakkeen autokuljetuksen logistiikka [Logistics for long-distance truck transport of forest chips]. In: Alakangas E, editor. VTT Symposium 221. The Yearbook 2002 of the Finnish Wood Energy Technology Programme; Sep 18–19; Jyväskylä. Espoo: VTT Technical Research Centre of Finland Ltd. p. 119–134. Finnish.

Sayama H. 2015. Introduction to the modeling and analysis of complex systems. Geneseo (NY): Open SUNY Textbooks, Milne Library.

SFS-EN. 2011a. 14778:en solid biofuels. Sampling. Helsinki: SFS.

SFS-EN. 2011b. 14780:en solid biofuels. Sample preparation. Helsinki: SFS.

Shabani N, Akhtari S, Sowlati T. 2013. Value chain optimization of forest biomass for bioenergy production: A review. Renew Sustain Energy Rev. 23:299–311.

Venäläinen P, Korpilahti A. 2015. HCT-ajoneuvoyhdistelmien vaikutus puutavarakuljetusten tehostamisessa–esiselvitys [The impact of HCT-vehicle on the efficiency of timber transport – Preliminary study]. Vantaa: Metsäteho Oy. Finnish.

Venäläinen P, Poikela A. 2016. D3.2.1-4 scenarios of energy wood transport fleet and back-haulage. Vantaa: Metsäteho Oy.

Windisch J, Väätäinen K, Anttila P, Nivala M, Laitila J, Asikainen A, Sikanen L. 2015. Discrete-event simulation of an information-based raw material allocation process for increasing the efficiency of an energy wood supply chain. Appl Energy. 149:315–325.

Virkkunen M, Kari M, Hankalin V, Nummelin J. 2015. Solid biomass fuel terminal concepts and a cost analysis of a satellite terminal concept. Espoo: VTT Technical Research Centre of Finland Ltd. VTT Technology 211.

Väätäinen K, Asikainen A, Eronen J. 2005. Improving the logistics of biofuel reception at the power plant of Kuopio city. Int J For Eng. 16:51–64.

Ye Y, Shen J, Bergqvist R. 2014. High-capacity transport associated with pre-and post-haulage in intermodal road-rail transport. J Transp Technol. 4:289–301.

Zamora-Cristales R, Boston K, Sessions J, Murphy G. 2013. Stochastic simulation and optimization of mobile chipping and transport of forest biomass from harvest residues. Silva Fenn. 47(5).

Zhang F, Johnson DM, Johnson MA. 2012. Development of a simulation model of biomass supply chain for biofuel production. Renew Energy. 44:380–391.

Publication IV

Aalto, M., Korpinen, O-J., Ranta. T.
Dynamic Simulation of Bioenergy Facility Locations with Large Geographical Datasets – a Case Study in European Region

Bulletin of the Transilvania University of Braşov
Vol. 10(59), pp. 1–10, 2017.

Bulletin of the *Transilvania* University of Braşov, Special Issue
Series II: Forestry • Wood Industry • Agricultural Food Engineering • Vol. 10 (59) No.1 - 2017

DYNAMIC SIMULATION OF BIOENERGY FACILITY LOCATIONS WITH LARGE GEOGRAPHICAL DATASETS - A CASE STUDY IN EUROPEAN REGION

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Abstract: *An agent-based simulation model was developed to account for the dynamic features of biomass feedstock logistics, including the large variation of supply and demand over time. The feedstock availability data is based on a geographical information system (GIS) analysis that covers 37 countries in Europe. The results may be used to optimize demand sites properties and compare the feasibility of different demand site locations. Out of eight locations, three were found have low fuel acquiring costs and other five could use long distance transportation to mitigate low supply of local biomass. Dynamic simulations flexibility makes it possible to integrate the model with a large database. The agent-based model with the large database from GIS provides a cost-efficient method to study and compare the geographical properties with a temporal factor of logistics, and it can be utilized as a tool for decision making of forest-based bioenergy facilities.*

Keywords: *forest biomass, agent-based, simulation, logistics, optimization.*

1. Introduction

The targets of reducing the use of fossil energy sources and replacing them with renewable energy sources have increased interest in new forest-based bioenergy and biorefining facilities. Before the facilities are built, analysis of feedstock availability and estimation of costs are carried out. There are many static analysis approaches (e.g. [5], [17]) that can be used for optimizing the location of the installation but, however, they usually exclude the dynamic elements of supply, demand, and logistics.

With dynamic simulation, a temporal factor of the demand-supply system can be included in the study. Agent-based simulation is a dynamic simulation method and it has been used for supply chain studies previously [8], [9] and [11].

Another reason to choose dynamic simulation is the flexible model design [3]. A disadvantage is the lower runtime performance that can be neglected to some extent by the model design or by increasing the computing capacity, which is nowadays relatively cheap. Due to complicated nature of the dynamic simulation, development and usage of the

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model requires an expert. The knowledge need of the model can be lowered by making the model easy to use, but the user has to have the ability to verify values that are used in the simulation.

Previous studies done with dynamic simulation approach have usually been location specific and only using local feedstock availability data. Location of the demand point in the model presented in this paper is user-defined showing how large database produced by GIS can be utilized with dynamic simulation study method allowing making comparisons between multiple locations.

The S2Biom project resulted in preparing a large database containing estimates of forest biomass availability in Europe [7], [8]. The database includes also estimated roadside costs for the available feedstock. The datasets cover EU28, Western Balkan Countries, Moldova, Turkey, and Ukraine.

During the designing phase of a new biomass utilization point, availability of the feedstock has to be counted but also logistics of acquiring the raw material have to be taken into account because logistics have a high impact on the operation costs of a biomass plant [13]. This factor can be included in a dynamic simulation model by using routing information that is, for example, provided by OpenStreetMap (OSM) [7].

This paper presents a dynamic simulation model that is developed by authors to solve the supply-demand problem. The model is based on a previous model that has been used for simulating agricultural feedstock logistics in India [8]. The same model concept is used for agricultural feedstock analysis [1].

The model has been modified to analyse forest-based bioenergy supply-demand problem and is still developed to count other feedstock types with needed operations. The model uses spreadsheet software for importing input values and exporting the results for further analyses.

Used feedstock data include primary forest fuels and forest residues that can be used for heat or power generation or refined to advanced biofuels. Supply chains of these materials have many models and there have been studies to improve the formers [1], [14] and [15]. Previous studies have excluded long-distance transportation and have not been sensitive enough to the stochastic supply delays [14]. These factors can be taken into account in the presented agent-based model.

2. Material and Methods

Feedstock availability information used in this paper have been reported by the S2Biom project [4], [18] and this paper focus is on presenting a method to use this data by a dynamic simulation model that uses the agent-based modelling method.

2.1. Data Preparation

Data provided by S2Biom is spatially distributed corresponding to NUTS3 regions. The database includes an assessment for seven categories of lignocellulosic biomass feedstocks. This study focused on "Wood production and primary residues from forests" [18]. The availability has been estimated for years 2012, 2020 and 2030.

The data include also different levels of harvest potentials: Technical, Base, High as well as eight different user-defined potentials. The dataset projected for the Base potential in 2020 was chosen for this study, and the data was reprocessed into two datasets: "Production from forests" and "Primary residues from forests".

The roadside costs were average weighted based on the availability of the biomass. Roadside costs include harvesting and forwarding feedstock to the roadside but exclude the contract costs.

The first reprocessed dataset, "Primary forest biomass", is production from the forest that includes stem and crown biomass from felling and thinning. The second dataset is primary residues from the forest and it is called "forest residues". This dataset includes logging residues from felling and thinning. The database includes also corresponding data for stumps, but it was excluded from the study due to different transportation and handling operations requirements.

For the simulation model, feedstock availability data had to be allocated to geographic supply points. This was done by creating a 5 × 5 km grid and using the centres of the grid cells as points of supply. The value of one point was the value of the respective NUTS3 region, divided by the total count of the grid points inside the region. Accordingly, all points inside the NUTS3 region got the roadside cost value of the region.

The computing power needed for the model running is relative to the amount of data imported to the model. To avoid unnecessary use of computing power, data from only one country per simulation run was used. Also, a maximum procurement radius was determined, lowering the number of points needed for the calculation process. Procurement radius was also used to determine the final proportions of biomass types. If the user-set portion of primary forest biomass from demand could not be fulfilled by the primary forest biomass, then the remaining demand was fulfilled by the available residues. If the share of residues could not be met, then the share was shifted to reserve fuel. Note that if residues could not be fulfilled and there are primary forest fuels available, the share wasn't shifted to primary forest fuels.

2.2. Description of the Simulation Model

The main purpose of the model was to produce location-specific data about feedstock logistics in different areas with multiple options for the location of utilization.

Agent-based modelling uses entities called agents to interact with each other and to create the simulation [12]. In the model, all agents are located in the Main-agent that includes the GIS-environment. There are: one demand point agent and multiple supply point agents set in this GIS-environment with agents called trucks that have the capacity to transport biomass with the later described as agent-called fuel entity.

Supply points accumulate fuel entities and call trucks to transport fuel entities to the demand point. The needed handling operations are performed at demand point on the fuel entities before they are used. An agent can carry information giving the possibility to have all costs of acquiring biomass carried by the fuel entity and add costs based on operations and fuel properties at the moment when the costs occur.

Input values are entered into the model through a spreadsheet file. There are two types of input values: values that are universal for all locations and location-specific values. Universal values include biomass properties and costs of the logistics operations. Location-specific values are coordinates of the utilization site, its annual demand (tonnes per year) and maximum procurement radius. These values are given in one row in the spreadsheet file.

The model imports the first row of the values to the model and runs a simulation. At the end of the simulation, the results are exported and the simulation run is repeated ten times with the same values so that the impact of stochastic events in the system can be discovered. Thereafter, new values are imported from the next row of the input file and the process is reiterated. Simulation is ended after running the last row of the input file.

The simulation run starts by placing a demand point in the system according to the coordinates given in input file. The acquisition of the biomass availability data from the right country is also based on the coordinates. The supply points inside the procurement radius are sorted out according to their proximity to the demand point and the biomass accumulation is calculated starting from the closest supply point. The proximity is calculated as the distance along the road network. The accumulation is terminated when the annual feedstock demand or the maximum procurement radius is met.

Feedstock availability data does not include other properties than the biomass amount (tonnes). The user of the model determines the energy content of one tonne of biomass, density of biomass before comminution and density of biomass after comminution. These values are universal for all simulation runs. The biomass properties are used to batch biomass to fuel entities agents.

Unlike the initial values imported from the spreadsheet file, truck fleet properties are given through the graphic user interface (GUI) of the model. These values are also universal, and they include the number and payloads of trucks. Payload determines how many fuel entities one truck can carry and the number of trucks determines how many truck agents can perform transportation simultaneously.

Trucks are set to operate between 8 AM and 5 PM on weekdays. In the morning trucks are sent from the demand point to retrieve a biomass load from the supply point if there is biomass available. Random supply point is selected using feedstock availability as weighing factor. This means that point's probability to be selected is point's supply amount divided by supply points' total availability in the system.

Trucks move to the supply point based on routing information (shortest route) and loads feedstock. Loading and slower speed of the forest road are considered to delay the truck for two hours at the supply point. After loading, truck returns to the demand point.

There is also a possibility to store feedstock at a buffer terminal next to the demand point. The user of the model defines the supply chain cases where trucks deliver their loads to the terminal instead of the demand point. When the truck has unloaded at a demand point or a terminal, the truck checks if there is more biomass at the supply point to retrieve. The truck operates also after 5 PM, but the trip has to begin latest at 5 PM.

Feedstock is comminuted at arrival to the demand point. The costs of comminution, purchasing and transportation are recorded and feedstock is stored in the storage. The amount of feedstock in the storage is recorded.

At the demand point, fuel is consumed every hour and the hourly consumption is based on monthly demand. If the storage goes below a defined level, more feedstock is called from the terminal. If there are no feedstock to fulfil the demand, reserve fuel is used. Reserve fuel's transportation or storing are not included in the model. Only energy content and price of reserve fuel is taken into account.

If the feedstock is transported to the terminal, it is comminuted to be ready for the use on short notice. When the demand point calls feedstock from the terminal, terminal trucks will transport fuel entities to the demand point for use. All costs of the terminal operations are included in the feedstock costs. Also, the annual cost of using the terminal is included in the result data if the terminal is used in the simulation.

The user may include transportation by other means than trucks (e.g. trains and vessels) in the input file. These deliveries are described in the system only as arrivals to the demand point or to the terminal. The properties of the arrivals by these means are set by defining the amount and biomass type that one delivery contains. The arrival frequency is set on a monthly basis. There may be as many transportation types as required.

The model keeps track on how much each feedstock type is used. Also, costs of feedstock procurement and reserve fuel use are recorded. These values are exported to an output spreadsheet file for further analysis.

3. Case Study

Eight locations where the International Symposium on Forestry Mechanization (FORMEC) meeting has been held were chosen for the case study (Fig. 1).

In these locations, a biomass demand of 100000 tons was applied (Table 1). It was assumed that these demand points could represent combined heat and power CHP plants. From the total biomass demand 80% was targeted at primary forest biomass and 20% of residues.

Biomass properties and costs of operations selected for this study are presented in Table 2. Values of fuel properties are estimations from fuels used in Finland [2]. Estimations for comminution costs are from Virkkunen et.al. [16] and cost of the transportation is estimated from the study of Korpilahti [10]. Transport capacity for primary forest materials was estimated to 30 m^3 loose and for residues to 20 m^3 loose. In the model, there were 30 trucks for primary fuels and 10 for residues.

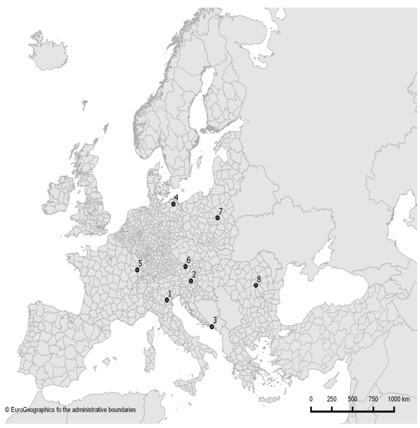

Fig. 1. *Locations of the demand points*

Input values of demand points Table 1

id	Latitude	Longitude	Proce. radius [km]	Annual demand [tons]
1	45.37	11.54	150	100 000
2	47.92	14.10	150	100 000
3	45.06	15.18	150	100 000
4	48.60	8.54	150	100 000
5	48.04	6.84	150	100 000
6	48.31	14.67	150	100 000
7	52.27	20.80	150	100 000
8	45.58	25.45	150	100 000

Fuel properties and costs estimations [2], [6] and [12] Table 2

Fuel type	Energy content of raw material [MWh/ton]	Truck transport cost [€/ton/km]	Comminution cost [€/ton]	Unloading costs [€/ton]	Density before comminution [ton/m^3$_{-loose}$]	Density after comminution [ton/m^3$_{-loose}$]
Primary	3,2	0,16	4,64	1,40	0,3	0,15
Residue	3,2	0,20	4,32	4,00	0,3	0,30

Forest biomass harvests vary over time and this was taken into account by using roundwood removal statistics from Finland [19] as seasonal supply distribution. Demand distribution was estimated to be highest during winter and lowest in the summer. This estimation was based on Finnish energy statistics [20]. For July, where maintenance of boilers usually takes place, demand was set to 0. Demand and supply distribution is presented in Fig 2.

Reserve fuel was assumed to be wood pellets with an energy content of 5 MWh/ton and with price 130 €/ton (Nordic Pellet Index PIX 18 Apr 2017).

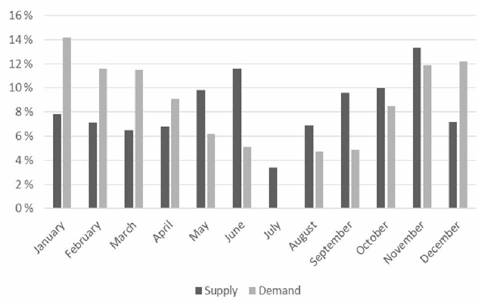

Fig. 2. *Supply and demand distributions*

4. Results and Revaluation

The case study was carried out in two simulation rounds. The results of the first round were used to estimate a better configuration of the demand points and simulation was run again with new values.

4.1. Results of Round 1

In three cases, less than 50% (i.e. less than 160 GWh/a) of the energy demand (320 GWh/a) was fulfilled by the biomass deliveries (Fig. 3). These locations have limited procurement area due to the proximity to shoreline (Fig. 1).

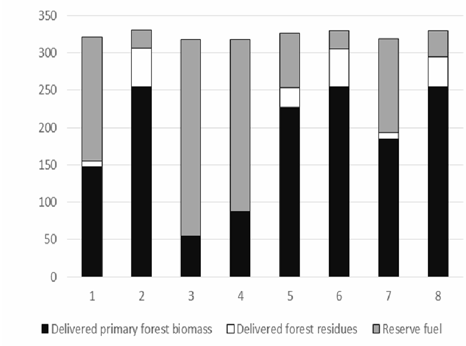

Fig. 3. *Distribution of feedstock use in Round 1*

The highest biomass shares were at demand points 2 and 6, which are both located in Austria. The third highest share was recorded at demand point 8, located in Romania. These locations have also the lowest average costs of feedstock supply (Fig. 4).

Due to the high price of the reserve fuel, locations with a low biomass shares had high costs. With current scenario needed storage for highest biomass share locations are over 60000 m^3 loose.

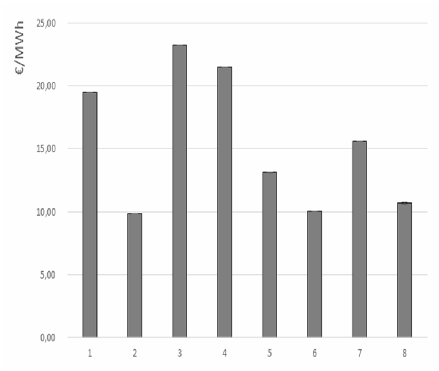

Fig. 4. *Average supply costs of biomass feedstock in Round 1*

4.2. Readjustment of Initial Data for Round 2

Based on the results of Round 1 it was assumed that supplementary deliveries by rail or waterway would benefit certain demand points in fulfilling the demand. It was also considered that this system would require a buffer terminal. The demand point was set a maximum biomass storage of 5000 m^3 loose. The storage of the terminal was unlimited.

Terminal fixed costs were set to 0 €/a and terminal trucks capacity was assumed to be 80 m^3 loose. There were three terminal trucks available and the cost of one trip was set to 3.00 €/ton.

Two long-distance vehicles, representing either train or vessel, were scheduled to arrive at all demand points. Both delivered primary forest biomass. The first transport type arrived four times every month and carried 500 tons of uncomminuted biomass. The second transport type arrived five times per month in high-demand season (October - March), carrying 1000 tons of uncomminuted biomass. Both transport types were defined to unload at the terminal. The price of the biomass arriving by these means was set to 50 €/ton.

4.3. Results and Conclusions of Round 2

Long-distance deliveries improved the use of biomass at locations where local supply had only a small share in fulfilling the demand in Round 1. However, there were still demand points where the use of reserve fuel remained high, such as locations 3 and 4 (Fig. 5).

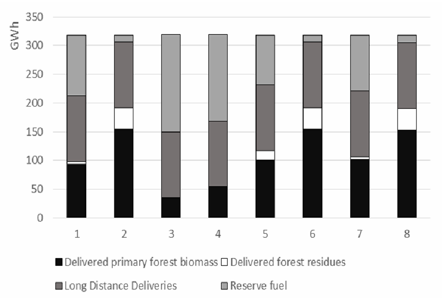

Fig. 5. *Distribution of feedstock use in Round 2*

In cases where local biomass supply mostly fulfilled the demand in Round 1, the local supply decreased. In these cases, also the average procurement costs increased from the results of Round 1 (Fig. 6). In cases where most of the demand was fulfilled with reserve fuel in Round 1, the costs decreased. Decrease resulted from shifting use of expensive reserve fuel to long distance deliveries.

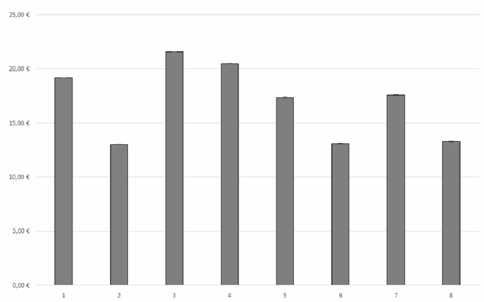

Fig. 6. *Average supply costs of biomass feedstock in Round 1*

Long-distance delivery price at the gate was slightly higher than that of local biomass but much lower than reserved fuel. In this study, the costs were crude assumptions and in the reality price would depend on many factors.

Terminal increased the cost of the supply chain but provided the possibility to have only 5000 m^3 loose storage at demand site. The highest local biomass supply to demand points 2, 6 and 8 resulted in the highest utilization of the terminal. In those cases, 82% of the delivered feedstock, including the long-distance deliveries, was supplied through the buffer terminal. In locations with the lowest usage of biomass, the terminal was only used for unloading long distance deliveries.

5. Discussion

The results of the case study indicate that geographical factors have a significant impact on the logistical arrangements in different places. Rural areas and especially coastlines near the demand points affect greatly how much feedstock is available in the surroundings. If local biomass supply cannot fulfil demand, long distance deliveries may be used to support the biomass supply. The feasibility of long distance transportation method is also case-specific. With good availability of local biomass, long distance deliveries may increase the cost of feedstock supply.

Using results from the Round 1, justifications to initial settings were made. It can be seen that all eight point that were studied have a potential for forest biomass demand points, but in some locations, the actual energy demand in real life would be lower than that of other locations due to climatic factors. Also, locations 3 and 4 should rely on long distance transportation, which could be feasible due to onshore for supply. These locations were close to coastline so it is a possibility to have marine transportations to the demand site.

To fulfil a high demand, a storage area is needed. Depending on local land costs and possibilities to have the storing area at demand point, a terminal may be used. The terminal will increase costs but it also provides the possibility to have a small storing area at demand site with high usage of local biomass. In the case study, infrastructure costs were not considered. A terminal with fixed costs would naturally increase total costs of supply.

Many initial values in the case study were taken from Finnish literature, while the demand points were located mainly in Central Europe. Only roadside cost and feedstock availability were based on spatially analyzed data [4]. The quality of result data could be improved by complementing the initial values with local data about e.g. vehicle properties and variation of feedstock supply and demand.

In the model, demand point is only receiving and using biomass based on demand. With more complicated systems, like multipurpose use of biomass and delivery of refined production, model needs to be modified. This will lead to more case specific models developed that need more specific data.

Dynamic simulation requirements of computing power and experts to use the model can be mitigated by the model design. Combined with a flexible design of dynamic simulation model, large databases can be utilized in future studies.

6. Conclusions

Dynamic simulation can be used to support decision making about the location of a new demand point using biomass as its feedstock. It gives versatile results and initial values may be easily variated. Because the locations are not optimized in the model it is recommended to use another method for location optimization prior to the simulation study.

Simulation gives the option to study many different scenarios fast and cost-efficiently. Possibility to adjust initial values based on previous results provides a way to easily optimize settings. With dynamic simulation combined with a large database, supply-demand problems can be studied using temporal and spatial effects, giving a unique tool for decision makers to use.

Acknowledgements

The authors would like to thank the persons that worked on the S2Biom project to gather feedstock data in the database. Special thanks to Dr. Sylvain Leduc who introduced the database to the authors.

References

1. Aalto M., Korpinen O.J., Ranta T., 2017. Biomass demand point location analyzer at regional level agent-based simulation. In: 26th European Biomass Conference and Exhibition, pp. 159-162.
2. Alakangas E., Hurskainen M., Laatikainen-Luntama J. et al., 2016. Suomessa käytettävien polttoaineiden ominaisuuksia. VTT Technology 258. Espoo: VTT Technical Research Centre of Finland Ltd., 263 p.
3. Becker M., Wenning B.-L, Görg C. et al., 2006. Agent-based and discrete event simulation of autonomous logistic processes. In: Proceedings 20th European Conference on Modelling and Simulation Wolfgang Borutzky, Alexandra Orsoni, Zobel Richards ΣECMS, pp. 566-571.
4. Datta P., Dees M., Elbersen B. et al., 2017. D1.5 The data base of biomass cost supply data for EU 28, Western Balkan Countries, Moldavia, Turkey and Germany, 26 p. [Online]. Available at: http://s2biom.alterra.wur.nl/doc/S2Biom_D1_5_v1_2_FINAL_19_04_2017_CP.pdf. Accessed on: August 31, 2017.
5. Ekşioğlu S.D., Acharya A., Leightley L.E. et al., 2009. Analyzing the design and management of biomass-to-biorefinery supply chain. In: Journal of Computers and Industrial Engineering, vol. 57(4), pp. 1342-1352.
6. Eriksson A., 2016. Improving the efficiency of forest fuel supply chains. Doctoral Thesis, Swedish University of Agricultural Sciences, Uppsala.
7. Haklay M., Weber P., 2008. OpenStreetMap: User-Generated Street Maps. In: IEEE Pervasive Computing, vol. 7(4), pp. 12-18.
8. Jäppinen E., Korpinen O.-J., Ranta T., 2015. Simulation Modelling in Biomass Logistics-Benefits, Challenges and Three Case Studies. In: 23rd European Biomass Conference and Exhibition, pp. 247-250.
9. Karttunen K., Väätäinen K., Asikainen A. et al., 2012. The operational efficiency of waterway transport of forest chips on Finland's Lake Saimaa. In: Silva Fenn., vol. 46(3), pp. 395-413.
10. Korpilahti K.A., 2015. Bigger vehicles to improve forest energy transport. In: Metsätehon tuloskalvosarja, vol. 3, 33 p.
11. Lättilä L., 2012. Improving transportation and warehousing efficiency with simulation-based decision support systems. Lappeenranta University of Technology.
12. Macal C.M., North M.J., 2005. Tutorial on agent-based modeling and simulation. In: Proceedings of the 2005 Winter Simulation Conference, Orlando, Florida, pp. 2-15.
13. Ranta T., Asikainen A., Lehikoinen M. et al., 2002. Metsähakkeen autokuljetuksen logistiikka.
14. Rauch P., 2013. Improving the primary

forest fuel supply chain. In: Bulletin of the Transilvania University of Brasov, Series II, vol. 6(55), no. 1, pp. 1-8.

15. Väätäinen K., Asikainen A., Eronen J., 2005. Improving the logistics of biofuel reception at the power plant of Kuopio city. In: International Journal of Forest Engineering, vol. 16(1), pp. 51-64.
16. Virkkunen M., Kari M., Hankalin V. et al., 2015. Solid biomass fuel terminal concepts and a cost analysis of a satellite terminal concept. VTT Technology 211. Espoo: VTT Technical Research Centre of Finland Ltd., 72 p.
17. Zhang F, Johnson D.M., Sutherland J.W., 2011. A GIS-based method for identifying the optimal location for a facility to convert forest biomass to biofuel. In: Biomass and Bioenergy, vol. 35(9), pp. 3951-3961.
18. ***, 2016. A spatial data base on sustainable biomass cost- supply of lignocellulosic biomass in Europe- methods & data sources, 171 p. [Online]. Available at: http://s2biom.alterra.wur.nl/doc/S2Biom_D1_6__version_23_Nov_2016.pdf. Accessed on: August 31, 2017.
19. ***, 2017a: OSF – Natural Resources Institute Finlann, 2016. Volumes and prices in industrial roundwood trade. [Online]. Available at: http://stat.luke.fi/en/volumes-and-prices-roundwood-trade. Accessed on: May 11, 2017.
20. ***, 2017b: Finnish Energy. Monthly Electricity Statistics. [Online]. Available at: http://energia.fi/en/current_issues_and_material_bank/material_bank/monthly_electricity_statistics.html#material-view. Accessed on: May 12, 2017.

Publication V

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Feedstock Availability and Moisture Content Data Processing for Multi-Year Simulation of Forest Biomass in Energy Production

Submitted to review: *Silva Fennica*

Feedstock availability and moisture content data processing for multi-year simulation of forest biomass in energy production

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Acknowledgements

This study is part of the project Improvement of forest chip quality and supply chain performance by means of a continuous quality measurement system (JATKUMO). Support from the European Unions Structural Funds have made it possible to conduct JATKUMO and this study.

Feedstock availability and moisture content data processing for multi-year simulation of forest biomass in energy production

Highlights:

A method to allocate forest biomass availability for a multi-year simulation model was developed;
The possibility to take into account the quality change of feedstock by moisture estimations was studied;
A method to estimate weather data for moisture estimation equations with fewer parameters was presented;

Abstract

Simulation and modeling have become more commonly used for forest biomass studies. Dynamic simulation models have been used to study the supply chain of forest biomass, with numerous different model. A multi-year model needs biomass availability data that is scattered spatially and temporally with an annual variation. This could be done by using enterprise data, but in some cases, this data cannot be acquired. Forest inventory data may be used to estimate forest biomass availability, but data must be processed in the correct form for the purpose of the model. A method for preparing forest inventory data for a multi-year simulation model using feedstock theoretical availability was developed. Methods for quality changes during roadside storage are also presented, including a possible parameter estimation to lowering the amount of data needed. Methods were tested case-by-case using the Biomass-Atlas and weather data from the Mikkeli weather station. A data processing method for biomass allocation produced a reasonable number of stands and feedstock amounts having a realistic annual supply with variation for the demand point. Estimations for moisture content changes using local weather data were found possible with moisture content estimation equations, but as estimations lower the accuracy of the results, it is recommended to avoid unnecessary estimations. The data preparations method presented may be used to generate a supply of forest biomass to the simulation model with reasonable accuracy using easily acquirable data. The prepared data needs to be validated and verified after preparation to ensure the correct behaviour of the model.

Keywords: Forest resources; Simulation; Forestry; Bioenergy; Geographic information system; Data analysis

1. Introduction

Forest biomass usage has high potential to lower fossil fuel usage and be a big contributor for energy supply (Demirbas et al. 2009; Wasajja and Chowdhury 2017). To have a high contribution for the energy supply system, the forest biomass supply must be secured for multiple years as the lifetime of power plants is long. The long-term availability of forest biomass is a concern, but through proper management, the long-term availability may be ensured in cases where higher demands are needed (Nabuurs et al. 2007).

The forest biomass supply chain may be studied with dynamic simulation if the available supply of the forest biomass is known. One way to get a supply of forest biomass is to use enterprise data as was done in a study by Windisch et al. (2015). This allows empirical data to use different scenarios. As enterprise data is not always available, the supply may be estimated by using databases (e.g LUKE 2018a; Datta et al. 2017), but this data must be processed for the simulation study to represent values that are as close to real life for the model’s needs. It is also good to note that the spatial analysis of the forest inventory may include errors (Islam et al. 2012; Holopainen et al. 2010) and validation of the data is required.

The forest biomass chain is a complex system including many activities (Rentizelas et al, 2009). The main activities of forest biomass generally pertain to harvesting, forest transportation, roadside storage, processing, transporting and conversion operations. Processing may be done in the early state, as roadside chipping, or after transporting, as chipping at the end user, or between transport operations, as chipping at the terminal. The interactions of machines and random events in the supply chain may cause delays (Asikainen 1995), leading to activities at the start of the chain affecting other activities. These issues make simulation studies widely used (Eriksson et al. 2014b; Väätäinen et al. 2005; Mobini et al. 2011; Aalto et al. 2018; Windisch et al. 2015; Ziesak et al. 2004).

To dynamically model a realistic forest biomass supply, feedstock must be scattered temporally and spatially. Using multiple years for the simulation time requires varying values instead of similar values for every year. Mobini et al. (2011) use the shelf-life model that was developed by MacDonald et al. (2007) and estimates volumes, areas and yield of the stands at the start of the simulation year. Mobini et al. (2011) also uses weather conditions, but only for the delay to the operations. This method allows changes to the supply volumes, but the locations of the stands do not change. Using forest inventory data to generate supply using statistics to stochastically distribute data spatially and temporally allows a more realistic spatial allocation. Spatial allocation of the supply affects the transportation costs, which have a high effect on the total costs of biomass (Allen et al. 1998a).

When stands are harvested, energy biomass is gathered, and it is normally left in the stand to dry. After that, the biomass is forwarded to the roadside for further transportation to the demand site. In energy usage, dry biomass is preferred as the moisture content affect the energy density of the biomass (Alakangas et al. 2016).

A modeling of the drying at the roadside storage is an easier option compared to the frequent manual sampling and measuring. Fixed drying functions have been developed (Sikanen et al. 2013), but they do not consider local weather. Measuring would give more accurate results, but simulation models cannot make measurements in multi-year supply forecast simulations, making an estimation of the drying a better option. The effect of moisture content may be studied by using different moisture levels of biomass (Kanzian et al. 2016; Eriksson et al. 2014a), but this results in more simulation runs which increases the computational load of the model significantly. That may be impractical because multi-year simulations already call for increased computing power.

Drying speed is highly affected by weather (Routa et al. 2015a). Important parameters are evaporation, precipitation, humidity, temperature, solar radiation and wind conditions (Routa et al. 2015a). As simulation models usually study the future effect, weather cannot be known. Long-term weather predictions could be used or past data may be used to develop an annual cycle that does not change significantly. Changes between years may be considered by stochastically selecting different years data to simulate weather.

The aim of the study was to develop a new data processing method to allocate biomass availability annually with spatial and temporal variation by using a forest inventory database. This allocation methods allows for a multi-year simulation without knowledge of the real forest stand locations and feedstock amounts. As the quality of biomass changes during storage and moisture content is the most important quality parameter (Alakangas et al. 2016), a possibility to use moisture estimation equations in the simulation model was studied. As these moisture estimation equations need a great amount of initial values and some are hard to come by, a possibility to use different estimations are investigated. Although using estimations increases the assumptions and decreases the validity of the model, these make it possible to develop a model with quality estimations and without numerous or impossible measurements.

2. Material and methods

To generate a forest biomass supply network that takes into account a temporal and spatial variation of supply locations and drying of the feedstock, the Geographical Information System (GIS) was used to generate a supply point grid that covers a predetermined supply area. The required parameters for drying models were estimated by using local weather data. The method may be used with fewer values, using more estimation, but this leads to less accurate results, thus making the simulation model less valid.

2.1 Feedstock availability data

The data preparation presented in this paper was done with data offered by Biomass-Atlas (LUKE 2018a), but any forest inventory -based estimates about theoretical availability may be used. The data was processed by having availability allocated in the centroids of the supply point grid of the supply area. The grid dimensions depend on the availability of data, the size of the supply area and the purpose of the simulation model. In this study, a 2km x 2km grid was used and the supply area was set to 120 km. A total of 3883 stand locations were generated with an annual supply of 78 500 m^3 of small diameter trees as whole trees and delimbed trees.

A number of the stands in the model should be selected resulting in the realistic amount of points, meaning that an annual number of stands should be less than the number of the centroids in the supply grid. With too large a number of points, this would lead to an amount of the biomass being too low in one point, and too small a number generates amounts that are too high per point. A good number of annual generated stands is affected by the density of the grid and how big is the supply area. If all availability of the database is used, the number of annual stands can be determined by dividing the total availability with the estimated average amount of feedstock in one stand. If availability is modified, number of stands may be determined by Eq. 1.

$$n_{sp} = \frac{\sum_{i=1}^{N_{sp}} V_{sp,i}}{V_{sp_{avg}}} \qquad \text{(Equation 1)}$$

The sum of the feedstock volume (Unit depends what units are used in the database, case study uses m^3) at one stand (V_{sp}) for the overall total number of stands (N_{sp}), is divided by the region's statistical average (or estimation) volume of the feedstock (Unit same as V_{sp} term) at one stand ($V_{sp,avg}$) giving a number of the stands that should be used in the model (n_{sp}). n_{sp} needs to be lower than N_{sp}.

Because only n_{sp} stands are created annually, the total amount of supply is reduced and this should be taken into account by increasing the available supply of one point. The amount of increase is a ratio of all stands and selected stands (Eq.2).

$$V_{msp,i} = \frac{N_{sp}}{n_{sp}} V_{sp,i} \qquad \text{(Equation 2)}$$

$V_{msp,i}$ is the feedstock amount at a stand in the model, while $V_{sp,i}$ is the feedstock amount from the database. With this increase, the annual supply should remain close to the statistical value acquired from the database. As stands are stochastically selected, some variation will occur in the total amount of the supply and, as the location of the supply changes, the total transport distances vary annually.

Feedstock data is static data and having annual dynamics is included, so the harvesting times of stands need to be included into the data. For this, statistical data may be used to stochastically schedule harvesting. In the study case, Finland statistics are used (LUKE 2018b). A monthly proportion of harvesting is used as the probability of harvesting happening at the particular month (Eq. 3).

$$P(M_i) = H_i \qquad \text{(Equation 3)}$$

$P(M_i)$ is the probability of harvesting at month i and H_i is a statistical proportion of harvesting at month i. This allocates the month of the harvest to a regional statistic value, but there can be stand-specific limitations for the harvesting. Certain stands can be harvested only in the winter when the ground is frozen. Other stands, usually on harder ground, can be harvested in the summer, but not in the thawing period. If stands have hard ground and they are near the road, it could be harvested anytime. Harvesting limitations can be taken account to allocate a probability of harvesting months of the stands with weather conditions to other months by location-specific factors. The day of the harvesting can be reasonably assumed to be uniformly distributed. This assumption does leave out the lower working amount of the weekends.

To test method, a supply area of 120 km and an estimation of 200 harvested stands annually, the harvested stands were allocated. As one set of 200 points represents a one year supply, 30 repetitions were constructed to see the variation between years. The transportation distance was estimated by the road network generated with GIS. The average distance was determined by road between selected stands to the demand point, located in the middle of the supply area, and comparing this to the average distance between all stands to the demand point.

2.2 Drying models

There are different drying estimation models for forest biomass developed (Routa et al. 2015b; Liang et al. 1996; Gigler et al. 2000; Erber et al. 2012; Murphy et al. 2012; Kim and Murphy 2013; Heiskanen et al. 2014). Routa et al. (2015b) validated a model for stem wood at roadside storage. The model uses a coefficient for evaporation (in *mm*) and precipitation (in *mm*) difference and adds a constant to get the daily moisture change (Eq. 4). The coefficient and constant are based on storage and wood type and these need to be estimated as case specific.

$$DMC = Coef\,(evaporation - precipitation) + const \qquad \text{(Equation 4)}$$

Heiskanen et al. (2014) developed a model that estimates moisture content by having coefficients for evaporation and precipitation. Moisture content at time *i* is calculated based on Eq. 5.

$$w_{i+1} = w_i + a\Sigma P / (w_i - w_{eq} + b) + c\Sigma E(w_i - w_{eq}) \qquad \text{(Equation 5)}$$

Moisture content at time *i+1* (w_{i+1}) is estimated by adding the affected drying to moisture content at time *i* (w_i). Drying is estimated with the effect of precipitation and evaporation. Affecting precipitation (*P*, in *mm*) is estimated by the difference between moisture content and equilibrium moisture content (w_{eq}), as this difference is scaled by how much wood may take moisture. There is constant *b* added to the divisor. The result of the division is scaled with coefficient *a*. The evaporation (*E*, in *mm*) estimation is also scaled with a difference of moisture and the equilibrium moisture content. Evaporation is multiplied by this and a coefficient, *c*. The coefficients *a*, *b* and *c* are storage and wood type specific and need to be estimated for all cases.

As one can see, there are common variables in the moisture prediction models as all forecast the same phenomena (Awadalla et al. 2004; Liang et al. 1996; Plumb et al. 1985). Drying estimation equations use precipitation values that are often measured as meteorological data, but evaporation measurements are rarer. Evaporation may be estimated with Penman-Monteith equation (Eq. 6) (Monteith 1981; Allen et al. 1998b), if there is no measured data available.

$$\lambda E = \frac{\Delta(R_n - G) + \rho_a c_p \frac{e_s - e_a}{r_a}}{\Delta + \gamma(1 + \frac{r_s}{r_a})} \qquad \text{(Equation 6)}$$

Eq. 6 uses net irradiance (R_n, in $W\ m^{-2}$), ground heat flux (G, in $W\ m^{-2}$), dry air density (ρ_a , in $kg\ m^{-3}$), specific heat capacity of air (c_p, in $J\ kg^{-1}\ K^{-1}$), the vapour pressure deficit of the air (e_s-e_a, in *Pa*), the rate of change of saturation specific humidity with air temperature (Δ, in $Pa\ K^{-1}$), the psychrometric constant (γ, in $Pa\ K^{-1}$), surface and aerodynamic resistances (r_s and r_a, in $s\ m^{-1}$) to calculate the energy rate of water evaporation (E, in $g\ s^{-1}m^{-2}$) multiplied with latent heat of vaporization (λ, in $J\ g^{-1}$). Due to the complications and needs of several parameters, this equation has been simplified many different ways (Linacre 1977; Salama et al. 2015; Gallego-Elvira et al. 2012). Linacre (1977) simplified Eq. 6 to form of Eq. 7.

$$E_0 = \frac{700T_m / (100 - A) + 15(T - T_d)}{80 - T} \qquad \text{(Equation 7)}$$

Eq. 7 uses elevation ($T_m = T + 0.006h$, *h* is the elevation (m) (Linacre 1977)), mean temperature (T, in °*C*), latitude (A, in degrees) and mean dew-point (T_d, in °*C*) to get evaporation rate (E_0, in $mm\ day^{-1}$). Most of these parameters are easily acquired from local weather station data. If the mean dew-point cannot be acquired, it may be estimated base on Eq. 8 (Linacre 1977).

$$T - T_d = 0.0023h + 0.37T + 0.53R + 0.35R_{ann} - 10.9^{\circ}C \qquad \text{(Equation 8)}$$

This includes R as a daily range of temperature and R_{ann} as the difference between mean temperatures of the coldest and hottest months (values in *°C)*. These values are easy to acquire from weather data.

Eq. 7 gives net evaporation at the lake that must be scaled to represent evaporation from on-ground biomass. To do this, the factor can be assigned to scale evaporation to the right. This factor is the equivalent Pan coefficient (E_p) that is used to convert measured evaporation from pan to evaporation from crops (Allen et al. 1998b). As roadside storages are near the forest and evaporation is from a wood surface, an estimation of 0.5 for E_p is reasonable.

To test the validity of the evaporation estimations, Eq. 7 with Pan coefficient 0.5 and polynomial fit for cumulative evaporation developed by Heiskanen et al. (2014) (Eq. 9, later called as VTT equation) were compared with year 2011 measured data from weather station (SYKE 2011) located at Mikkeli.

$$\Sigma E = 0.0476x^5 - 1.5947x^4 + 17.865x^3 - 73.301x^2 + 126.47x - 70.151 \quad \text{(Equation 9)}$$

Fit uses x as the numerical value of month (January = 1, February =2...). The coefficient of determination R^2 = 0.9993. Eq. 9 fit has been compared with weather data from Mikkeli during the years 1991-2005 and from Havumäki for the year 2012 by Heiskanen et al. (2014). For investigating moisture estimate equations, they are compared with each other using weather data acquired from the Mikkeli weather station and the same initial moisture content.

3. Results

As previously stated, for the testing method 200 harvesting stands were selected to be the annual number of stands for a 120 km supply area. These are used to test the feedstock allocation and, for drying, estimations are tested by comparing them with measured values. As drying equations use weather data, the effect of using estimations for these values was also tested.

3.1 Feedstock allocation

Results from the stand allocation indicate the number of stands generated, distributed between months (Fig. 1). The statistical average (Line at Fig. 1) is little higher than the modeled number of stands. This is due to some stands having an availability of zero.

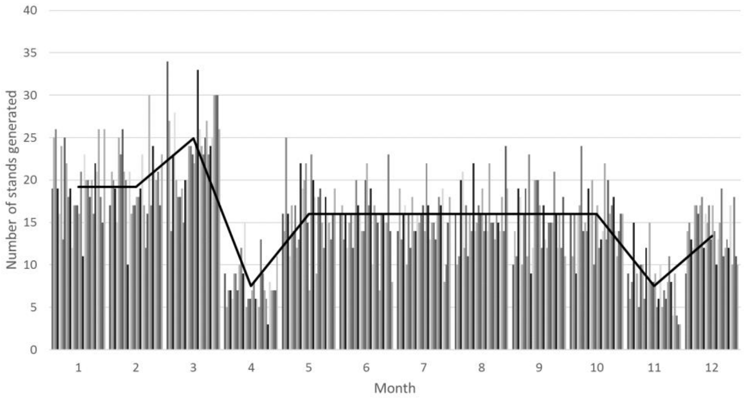

Figure 1. Number of stands created per month in 30 repetitions (Line: Statistical average).

The amount of available feedstock varied between repetitions (Fig. 2). The average of the variation was -1.45 %, showing a need to compensate for the zero availability error mentioned above. The highest available amount of the feedstock was 11%, higher than the statistical average. The lowest availability was 22%, lower than the statistical amount.

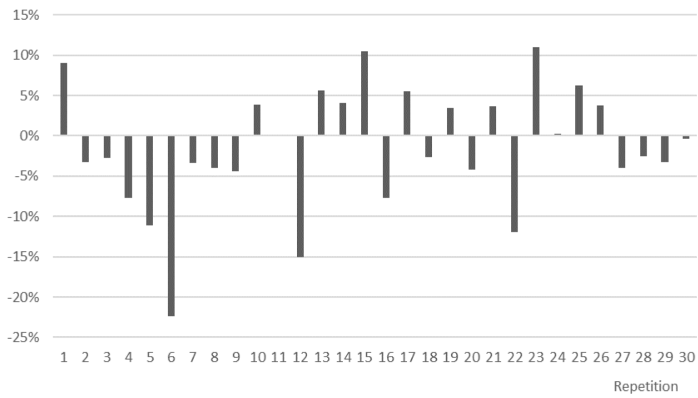

Figure 2. Deviation of simulated biomass harvest volumes per simulation repetitions from the annual average of the total stand population.

The distance from the selected stands to the demand point varied between different years (Fig. 3). The average of all repetitions was 0.85% less than the average of all possible stands to demand point routes.

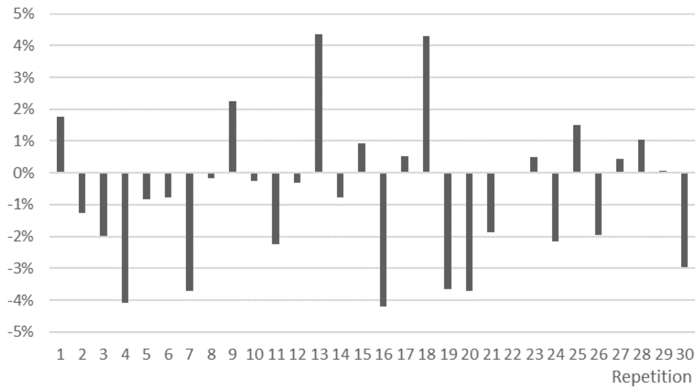

Figure 3. Deviation of simulated transport distances per simulation repetitions from the total of all stand to demand point transport routes.

3.2 Weather data validation

Precipitation was taken from Mikkeli weather data and factors of the drying models (Eq.4 and Eq. 5) are from literature and assumed to be corresponding. Evaporation was estimated by using Eq. 7 with a Pan coefficient and needs to be validated. The values were estimated with weather data from the weather station at Mikkeli (FMI 2011) and measurements for the year 2011 were taken. The elevation was set to 1 meter and the latitude to N60°.

The monthly evaporation rates are presented at Fig. 4. It can be noted that measurements have not been done during the cold months as the values are zero between December to April. Eq. 9 gives a continuous line. This may not be true as weather is not always continual and changes from the annual average occur often, as happens with the evaporation estimation by Eq. 7 in which July gets an unusually high value. The same effect can be seen from measured data. Eq. 7, which also gives negative values during cold months, but this value should be zero as the temperature is below zero and the evaporation may be assumed to be zero.

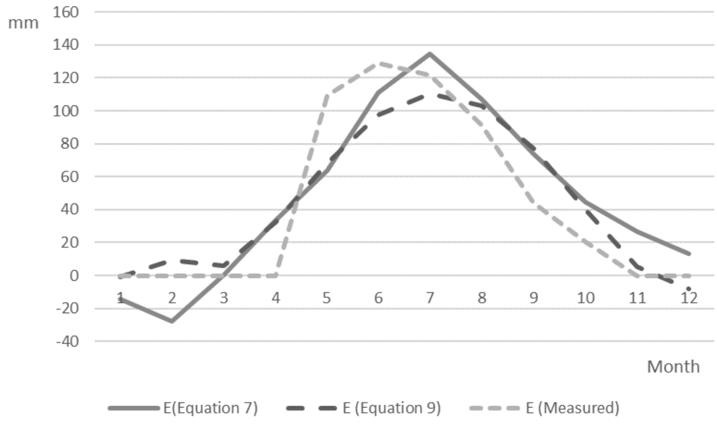

Figure 4. Estimated evaporations and measured evaporation from the Mikkeli weather station.

Using weather data from 2011 and estimating the moisture content for two years of forest biomass that have initial moisture content 45% with Eq. 4 using *Coef* = 0.062 and *Const* = 0.039 provides a corresponding uncovered pine stem storage (Raitila et al. 2015). Same estimation was done to Eq. 5 with constants a = 0.0008, b = 5 and c = 0.002 corresponding to the delimbed pine stem storage (Raitila et al. 2015). It can be seen that both methods produce similar results for the first year (Fig. 5). During winter, Eq. 4 is not valid (Routa et al. 2015b) and the moisture content is estimated to stay constant which leads to a small error. Routa et al. (2015b) suggest a 5%-unit increase for the winter time, which would correct the error. For longer periods, the error increases as there is no limit to how dry the forest biomass may get. With Eq. 5, the equilibrium moisture terms slows down the drying and prevents the moisture content from dropping under the equilibrium moisture value.

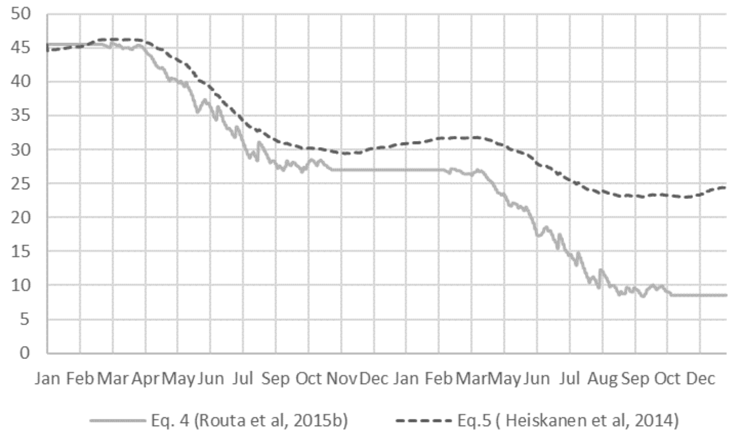

Figure 5. Moisture content estimations with Eq. 4 and Eq. 5 using 2011 weather data from Mikkeli weather station and starting moisture 45%.

4. Discussion

The method produced forest biomass availability with an annual variation. The lowest availability, produced by the method, was 22% lower than the statistical amount. This was a high difference but possible in real life, although uncommon. This effect was enhanced by having zero availability points and eliminating this would lead to better results. A number of zero availability points in dataset may be taken account by adding a factor to the Eq. 2 if a proportion of zero availability supply points is known. A better option is to eliminate zero points beforehand.

Allocating points in the grid and selecting random points annually did produce a variance in the transport distance. This indicates the allocation of points to be stochastic and suited for multi-year simulations. Having a stand allocated to the centroids of the grid is only one possible allocation method of the locations. If the real stand locations of the supply area are known, these locations can be used instead of the centroid of the grid. This is possible by using a forest information resource that includes the locations of the stands or if the enterprise has locations of stands that are in their supply area. Having real locations of the stand gives more realistic roadside locations and, if the information includes the area of the stand, it may be used as a factor to allocate initial supply amounts from the forest inventory. The process to increase the availability of one stand would stay the same.

Moisture estimation equations show the difference between each other. The Eq. 4 seems better suited for shorter storage times as longer storing would lead to even negative moisture contents and that is not possible. Eq. 4 also shows more variation on a daily scale that is beneficial for the simulation of short storing times. If the storing time is assumed to be years, Eq. 5 would be better for these cases as the daily changes are not as relevant. As this study does not have real storage to compare results, the validity of the models cannot be proven. Although, Raitila et al. (2015) compared both moisture content estimations with measured validation results from three validation storages and found both estimation methods rendering good results with a variation of 0.4 to 3.2%-unit for Eq. 4 and 0.2 to 2.8%-unit for Eq. 5. In both cases, the used constants and coefficients affect the results greatly and getting corresponding values for the simulation situation may be challenging.

A monthly number of harvested stands and amount of the available feedstock was possible to generate by the preprocessing method described in this paper. Lowering the number of stands toward a more realistic amount allows for multi-year studies that use biomass availability database data as initial values. Forest operations may be included by modeling with machinery productivity. If this is done, it is important to have the stands' feedstock amounts correspond to real life stands. The method must use regional data and, depending on the data, some adjustment needs to be done, but the allocation of the stands and available feedstock may be done with reasonable accuracy by the presented method.

As the simulation model imitates real life operations, it is good to use real-life data like measured or enterprise operative data, but these data cannot always be acquired and, if the simulation is a theoretical situation, this data does not exist. This forces an estimate of the data and this should be done using statistically valid data and should process the data for the simulation model as closely as possible to the real-life equivalent. For forest biomass, the supply needs to scatter temporally and spatially with the correct availability of harvesting stands. The data preparation method presented allocates the harvested stands to the supply area producing a valid supply network that includes a variation of the feedstock amount and locations of the points.

The allocation of the supply points by using a method including stochastically elements allows the representation of a real life annual variation of the harvested forest stands. Having the possibility to conduct a study for multiple years enables the inclusion of long-time planning, yearly variations of feedstock and annual transport cost variations in the study. Taking into account the uncertainly of feedstock availability and demand requirements, for example by storage terminal, requires multiple years as big storage levels have annual changes. Sahoo and Mani (2015) conducted a multi-year biomass supply chain study using Miscanthus crop as feedstock. The annual feedstock availability was changed between years with static values and the locations were keep the same. This was possible as the crop biomass supply locations do not change as dramatically as the forest biomass.

Eriksson et al. (2017) use random locations inside the circle to generate forest stands around demand location. Although this gives variable transportation distance, it does not take local variables to account like the amount of the feedstock at the location or harvesting time allocations due to weather variables. In addition, limiting factors for supply areas are not taken into account (e.g. water bodies or urban areas).

As the moisture content of the feedstock affects the amount of the energy stored, the moisture content change should be taken into account. There are different possible methods, but these may increase the computational power requirements or do not take account local weather variations. Windisch et al. (2015) used drying curves that are less demanding for computational power than estimation equations but do not consider local weather variations.

Using weather station data and equations to estimate moisture content, the effect of weather can be accounted for by a quality change of the forest biomass. These results can be acquired with a different amount of the available data by using equations to estimate values that are less often measured or are complicated to calculate. The accuracy of the results and the model will be lowered with estimations and it is recommended to avoid unnecessary estimations. The used estimations should be validated and verified case-specifically as the level of abstraction and the purpose of the simulation model affects the importance of the data preparation.

References

Aalto M., Korpinen OJ., Loukola J., Ranta T. (2018). Achieving a smooth flow of fuel deliveries by truck to an urban biomass power plant in Helsinki, Finland –an agent-based simulation approach. International Journal of Forest Engineering 29(1):21-30. https://doi.org/10.1080/14942119.2018.1403809.

Alakangas, E., Hurskainen, M., Laatikainen-Luntama, J., & Korhonen, J. (2016). Properties of indigenous fuels in Finland. (VTT Technology; Vol. 272). Espoo: VTT Technical Research Centre of Finland.

Allen, J., Browne, M., Hunter, A., Boyd, J., & Palmer, H. (1998a). Logistics management and costs of biomass fuel supply. International Journal of Physical Distribution & Logistics Management, 28(6), 463-477. https://doi.org/10.1108/09600039810245120.

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998b). Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. Fao, Rome, 300(9), D05109.

Asikainen, A. (1995). Discrete-event simulation of mechanized wood-harvesting systems. Joensuu: University of Joensuu. 86 p.

Awadalla, H. S. F., El-Dib, A. F., Mohamad, M. A., Reuss, M., & Hussein, H. M. S. (2004). Mathematical modelling and experimental verification of wood drying process. Energy Conversion and Management, 45(2), 197-207. https://doi.org/10.1016/S0196-8904(03)00146-8.

Datta P., Dees M., Elbersen B., Staritsky I. (2017). The data base of biomass cost supply data for EU 28, Western Balkan Countries, Moldova, Turkey and Ukraine. Project Report. Chair of Remote Sensing and Landscape Information Systems, Institute of Forest Sciences, University of Freiburg, Germany. 25p.

Demirbas, M. F., Balat, M., & Balat, H. (2009). Potential contribution of biomass to the sustainable energy development. Energy Conversion and Management, 50(7), 1746-1760. https://doi.org/10.1016/j.enconman.2009.03.013.

Erber, G., Kanzian, C., & Stampfer, K. (2012). Predicting moisture content in a pine logwood pile for energy purposes. Silva Fennica, 46(4), 555-567.

Eriksson, A., Eliasson, L., Hansson, P. A., & Jirjis, R. (2014a). Effects of supply chain strategy on stump fuel cost: a simulation approach. International Journal of Forestry Research, 2014. http://dx.doi.org/10.1155/2014/984395.

Eriksson, A., Eliasson, L., & Jirjis, R. (2014b). Simulation-based evaluation of supply chains for stump fuel. International Journal of Forest Engineering, 25(1), 23-36. https://doi.org/10.1080/14942119.2014.892293.

Eriksson, A., Eliasson, L., Sikanen, L., Hansson, P. A., & Jirjis, R. (2017). Evaluation of delivery strategies for forest fuels applying a model for Weather-driven Analysis of Forest Fuel Systems (WAFFS). Applied energy, 188, 420-430. https://doi.org/10.1016/j.apenergy.2016.12.018.

FMI. (2011) Weather and sea, download observations. https://en.ilmatieteenlaitos.fi/download-observations/. Finnish Meteorological Institute. [Cited 16 Oct 2018].

Gallego-Elvira, B., Baille, A., Martin-Gorriz, B., Maestre-Valero, J. F., & Martinez-Alvarez, V. (2012). Evaluation of evaporation estimation methods for a covered reservoir in a semi-arid climate (south-eastern Spain). Journal of hydrology, 458, 59-67. https://doi.org/10.1016/j.jhydrol.2012.06.035.

Gigler, J. K., van Loon, W. K., Seres, I., Meerdink, G., & Coumans, W. J. (2000). PH—postharvest technology: drying characteristics of willow chips and stems. Journal of Agricultural Engineering Research, 77(4), 391-400. https://doi.org/10.1006/jaer.2000.0590.

Heiskanen VP., Raitila J., Hillebrand K. (2014). Varastokasassa olevan energiapuun kosteuden muutoksen mallintaminen [Modeling of moisture change in energy wood in a storage]. Report VTT-R-08637-13

Holopainen, M., Vastaranta, M., Rasinmäki, J., Kalliovirta, J., Mäkinen, A., Haapanen, R., ... & Hyyppä, J. (2010). Uncertainty in timber assortment estimates predicted from forest inventory data. European Journal of Forest Research, 129(6), 1131-1142. https://doi.org/10.1007/s10342-010-0401-4.

Islam, M. N., Pukkala, T., Kurttila, M., Mehtätalo, L., & Heinonen, T. (2012). Effects of forest inventory errors on the area and spatial layout of harvest blocks. European journal of forest research, 131(6), 1943-1955. https://doi.org/10.1007/s10342-012-0645-2.

Kanzian, C., Kühmaier, M., & Erber, G. (2016). Effects of moisture content on supply costs and CO2 emissions for an optimized energy wood supply network. Croatian Journal of Forest Engineering: Journal for Theory and Application of Forestry Engineering, 37(1), 51-60.

Kim, D. W., & Murphy, G. (2013). Forecasting air-drying rates of small Douglas-fir and hybrid poplar stacked logs in Oregon, USA. International Journal of Forest Engineering, 24(2), 137-147. https://doi.org/10.1080/14942119.2013.798132.

Liang, T., Khan, M. A., & Meng, Q. (1996). Spatial and temporal effects in drying biomass for energy. Biomass and Bioenergy, 10(5-6), 353-360. https://doi.org/10.1016/0961-9534(95)00112-3.

Linacre, E. T. (1977). A simple formula for estimating evaporation rates in various climates, using temperature data alone. Agricultural meteorology, 18(6), 409-424. https://doi.org/10.1016/0002-1571(77)90007-3.

LUKE. (2018a). Biomass-atlas. https://www.luke.fi/biomassa-atlas/en/. Natural Resources Institute Finland. [Cited 16 Oct 2018].

LUKE. (2018b). Industrial roundwood removals and labour force - harvesting volumes of energy wood per month. http://statdb.luke.fi/PXWeb/pxweb/en/LUKE/. Natural Resources Institute Finland. [Cited 16 Oct 2018].

MacDonald, A. J. (2007). Estimated costs for harvesting, comminuting, and transporting beetle-killed pine in the Quesnel/Nazko area of central British Columbia. In Proceedings of the International Mountain Logging and 13th Pacific Northwest Skyline Symposium, Corvallis, OR (pp. 208-214).

Mobini, M., Sowlati, T., & Sokhansanj, S. (2011). Forest biomass supply logistics for a power plant using the discrete-event simulation approach. Applied energy, 88(4), 1241-1250. https://doi.org/10.1016/j.apenergy.2010.10.016.

Monteith, J. L. (1981). Evaporation and surface temperature. Quarterly Journal of the Royal

Meteorological Society, 107(451), 1-27. https://doi.org/10.1002/qj.49710745102.

Murphy, G., Kent, T., & Kofman, P. D. (2012). Modeling air drying of Sitka spruce (Picea sitchensis) biomass in off-forest storage yards in Ireland. Forest Products Journal, 62(6), 443-449. https://doi.org/10.13073/FPJ-D-12-00096.1.

Nabuurs, G. J., Pussinen, A., Van Brusselen, J., & Schelhaas, M. J. (2007). Future harvesting pressure on European forests. European Journal of Forest Research, 126(3), 391-400. https://doi.org/10.1007/s10342-006-0158-y.

Plumb, O. A., Spolek, G. A., & Olmstead, B. A. (1985). Heat and mass transfer in wood during drying. International Journal of Heat and Mass Transfer, 28(9), 1669-1678. https://doi.org/10.1016/0017-9310(85)90141-3.

Raitila, J., Heiskanen, V. P., Routa, J., Kolström, M., & Sikanen, L. (2015). Comparison of moisture prediction models for stacked fuelwood. BioEnergy Research, 8(4), 1896-1905. https://doi.org/10.1007/s12155-015-9645-7

Rentizelas, A. A., Tolis, A. J., & Tatsiopoulos, I. P. (2009). Logistics issues of biomass: the storage problem and the multi-biomass supply chain. Renewable and sustainable energy reviews, 13(4), 887-894. https://doi.org/10.1016/j.rser.2008.01.003.

Routa, J., Kolström, M., Ruotsalainen, J., & Sikanen, L. (2015a). Precision measurement of forest harvesting residue moisture change and dry matter losses by constant weight monitoring. International Journal of Forest Engineering, 26(1), 71-83. https://doi.org/10.1080/14942119.2015.1012900.

Routa, J., Kolström, M., Ruotsalainen, J., & Sikanen, L. (2015b). Validation of prediction models for estimating the moisture content of small diameter stem wood. Croatian Journal of Forest Salama, M. A., Yousef, K. M., & Mostafa, A. Z. (2015). Simple equation for estimating actual evapotranspiration using heat units for wheat in arid regions. Journal of Radiation Research and Applied Sciences, 8(3), 418-427. Engineering: Journal for Theory and Application of Forestry Engineering, 36(2), 283-291. https://doi.org/10.1016/j.jrras.2015.03.002.

Sahoo, K., & Mani, S. (2015, December). GIS based discrete event modeling and simulation of biomass supply chain. In 2015 Winter Simulation Conference (WSC) (pp. 967-978). IEEE.

Sikanen L., Röser D., Anttila P., Prinz R. (2013). Forecasting algorithm for natural drying of energy wood in forest storages. Forest Energy Observer. Study Report 27.

SYKE. (2011). Hydrologiset kuukausitilastot [Hydrological monthly statistics]. http://wwwi3.ymparisto.fi/i3/paasivu/fin/etusivu/etusivu.htm. Natural Resources Institute Finland. [Cited 16 Oct 2018]

Väätäinen, K., Asikainen, A., & Eronen, J. (2005). Improving the logistics of biofuel reception at the power plant of Kuopio city. International Journal of Forest Engineering, 16(1), 51-64. https://doi.org/10.1080/14942119.2005.10702507.

Wasajja, H., & Chowdhury, S. D. (2017). Evaluation of advanced biomass technologies for rural energy supply. In AFRICON, 2017 IEEE (pp. 1272-1276). IEEE. https://doi.org/10.1109/AFRCON.2017.8095665.

Windisch, J., Väätäinen, K., Anttila, P., Nivala, M., Laitila, J., Asikainen, A., & Sikanen, L. (2015). Discrete-event simulation of an information-based raw material allocation process for increasing the efficiency of an energy wood supply chain. Applied energy, 149, 315-325. https://doi.org/10.1016/j.apenergy.2015.03.122.

Ziesak, M., Bruchner, A. K., & Hemm, M. (2004). Simulation technique for modelling the production chain in forestry. European Journal of Forest Research, 123(3), 239-244. https://doi.org/10.1007/s10342-004-0028-4.

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ISBN 978-952-335-382-4
ISBN 978-952-335-383-1 (PDF)
ISSN-L 1456-4491
ISSN 1456-4491
Lappeenranta 2019