LUT University
School of Engineering Science
Erasmus Mundus Master's Program in Pervasive Computing & Communications for Sustainable Development (PERCCOM)

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PROACTIVE ADAPTATION OF BEHAVIOR FOR SMART CONNECTED OBJECTS

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- Master in Pervasive Computing and Communications for Sustainable Development (Luleå University of Technology)

ABSTRACT

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Proactive Adaptation of Behavior for Smart Connected Objects

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The great amount of generated data from IoT infrastructures in Smart Cities, if properly leveraged, presents the opportunity to shift towards more sustainable practices in rapidly increasing urban areas. Reasoning upon this data in a proactive way, by avoiding unwanted future events before they occur, leads to more efficient services. For a system to do so, a robust reasoning model, able to anticipate upcoming events and pick the most suitable adaptation option is needed. Recently deployed smart waste management systems for monitoring and planning purposes report substantial cost-savings and carbon footprint reductions, however, such systems can be further enhanced by integrating proactive capabilities. This work proposes a novel reasoning model and system architecture called ProAdaWM for more effective and efficient waste operations when faced with severe weather events. A Bayesian Network and Utility Theory, as the basis of Decision Theory, are utilized to model the uncertainties and handle how the system adapts; the proposed model utilizes weather information and data from bin level sensor for reasoning. The approach is validated through the implementation of a prototype and the conduction of a case study; the results demonstrate the expected behavior.

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LIST OF SYMBOLS AND ABBREVIATIONS

AFW	Average Consumed Fuel per Liter of Collected Waste
API	Application Programming Interface
BN	Bayesian Network
DAG	Directed Acyclic Graph
DS	Design Science
DSRM	Design Science Research Methodology
EU	Expected Utility
FER	Fuel Efficiency Ratio
GHG	Greenhouse Gas
GIS	Geographic Information System
GPS	Global Positioning System
HTTP	Hypertext Transfer Protocol
ICT	Information and Communication Technologies
IoT	Internet of Things
IS	Information Systems
MEU	Maximum Expected Utility
REST	Representational State Transfer
RFID	Radio-frequency identification
SDG	Sustainable Development Goals
SMHI	Swedish Meteorological and Hydrological Institute
WM	Waste Management

1 Introduction

This chapter introduces the main research domains that this thesis is related to, namely waste management (WM) in smart cities and proactive adaptation of behavior in Internet of Things (IoT) ecosystem. This is followed by a presentation of the research motivation as well as the definition of the research questions and objectives. The research methodology is also presented in this chapter.

1.1 Introduction

With the fast development pace of urban areas and their population growth, effective and sustainably sound waste management practices are becoming a must for cities in a global scale. Not only the estimated waste amount of 3.4 billion tons annually by 2050, is making this a critical issue that needs urgent action, but also its expected 2.6 billion tonnes of CO_2 emissions by 2050 [7]. Global action has demonstrated that Information and Communication Technologies (ICT) are becoming a key component to mitigate the negative effects current waste related operations are posing on the environment and on the citizen's life quality [7, 8]. From sensor equipped waste containers, to analytics and decision support systems, ICT offers a plethora of opportunities, spanning from hardware infrastructure to software tools. The latter serve the purpose of both gaining insights on the waste production, collection and disposal processes, and also taking decisions for conducting these processes in the most efficient and effective way.

In the recent years enabling ICT solutions for urban waste management are rapidly developing under frameworks and directives for smart cities [9]. The definition of a smart city is tightly connected to sustainability, by being able to develop "in a manner that meets the needs of the future without compromising the ability of future generations to meet their own needs" [10]. Recent developments in IoT are the main drivers behind the shift towards Smart Cities. The "Anytime, Anyplace with Anything and Anyone connected things " IoT paradigm can enable smart city services in several use-cases such as structural health of buildings, waste management, air quality, noise monitoring, traffic congestion, smart parking, smart lighting [11] and more.

The continuous deployment of IoT infrastructures is associated with great amounts of generated data coming from interconnected sensors that have turned everyday objects into smart connected devices. This abundance of raw data presents an opportunity for stakeholders and systems to decide and act proactively by anticipating their future needs. However, gaining the right knowledge from the available data requires proper and robust reasoning models that conduct inference and are aware of the user's goals. Proactive computing presents a way for enhancing data-driven systems by reacting to events or unwanted predicted situations before they occur [4], thus yielding significant benefits by offering a seamless service [5]. The term was first introduced by Tennenhouse in 2000 as a new type of computing that removed the human intervention form the interaction loop of a system that is tightly connected to the physical world by sensors and actuators[12]. Our work investigates methods of proactive adaptation, how it has been, or can be integrated, into smart WM scenarios.

1.2 Motivation

Given these threatening trends of the damage improper waste handling is causing to the environment, stringent regulations are posed worldwide to shift towards environmentally sound and sustainable waste management practices. Enhanced infrastructure is needed by the responsible companies and municipalities to tackle this problem. Adopting an information system that relies in new technologies is key for improved collection processes at municipal level [8]. In addition to that, a basic understanding of the waste generation characteristics such as amount and composition of the produced materials, is crucial to provide these services effectively [13].

Many municipality and news reports [14, 15, 16, 17, 18] describe the susceptibility and unpreparedness of the waste management instances towards severe *weather events* in developed countries. The World Bank Report explicitly states that:

"Waste management systems should take into account potential extreme weather such as heavy storms that may cause the collapse of formal or informal waste facilities or damage urban infrastructure." [7]

Given these problems, there is a need for an anticipatory policy to handle waste disposal

in an efficient way when severe weather events are present as well as inform the citizens and drivers accordingly. In literature or commercial solutions, bins to be emptied are selected either on some level threshold [19] or their predicted level of waste [20], however, this approach would not be sufficient unless weather events and their characteristics are explicitly considered in the adaptation process. Methods for proactive recommendations or adaptation of behavior of the connected devices can be integrated with existing system infrastructures, to make up for this problem and offer robust solutions towards severe weather events.

1.2.1 Scenario

In January 2011 a snowstorm in New York produced 20 inches of snow paralyzing the city's transport means reducing its ability to clear the snow from the streets and conduct the waste collection operations as planned [13]. In addition to that, even once the streets are cleared, and transportation is still possible for smaller vehicles, due to safety reasons, the drivers of the collection vehicle skip certain trash bins until the street conditions visibly improve; this causes delays in the disposal of waste in certain areas. As reported, once the collection processes restart, the available resources (drivers, collection vehicles) might not be enough to handle all the workload in a timely manner, leading to dissatisfied customers and a low service quality. Problems arise even when rescheduling takes place, as citizens are not always informed on time to take their household bins out or not. According to Skellefteå municipality information is crucial for smooth operations. Especially in residential areas, the bins to be serviced are selected on a fixed repetitive schedule, hence citizens tend to strictly follow that schedule unless notified of any disruptions. Consider the following user stories:

*Ada is a **citizen** who lives in a residential area in Skellefteå. There has been heavy snow for one week and she finally decided to take her trash out. But when Ada approached the disposal area, she could feel a bad smell coming from the bins, as well as see some trash outside. Apparently the bins had not been emptied during the scheduled week day due to the heavy snow that had blocked the road for the collection truck.*

***The waste management company** has recently adopted new technologies in their infrastructure for monitoring their processes and operations. Currently they are working with*

fixed schedules, for e.g. residential areas are visited once or twice weekly depending on the population of the area, whereas central and business areas with restaurants and shops are visited every three to four days due to the increased amount of waste that it is produced there. However, it often happens that during winter with heavy snow many streets are blocked, and their schedules are not synchronized with that of the snow cleaning company, so too much waste remains uncollected in some areas. Except having a negative impact to the environment, since waste can be spread around and never collected, uncollected also poses a danger to the public health if not disposed correctly. The waste management company needs to avoid this.

Oscar works as a ***truck driver*** *in the waste management company. Unfortunately, that day in January he had to visit a collection area twice because certain streets of it had not been cleared from snow. This delayed the collection routine for another area until the next day. It often happens during winter that his work is hindered by weather factors. Sometimes, if he sees that some street is too icy, or has cars parked in it, he decides that it is safer to skip that street and come back later to avoid any accident. Quite often it happens for him to work extra hours once the weather conditions have recovered.*

1.2.2 Stakeholders

This section identifies the involved stakeholders and their interests, the latter have been formulated based on the reviewed literature and communications with Skellefteå municipality.

- Municipality

  The municipality is concerned with providing quality services to its citizens, waste collection and disposal being one such service. In addition to that it has to report to higher instances on how optimized their operations are and the impact they have on the environment. It is crucial for the municipality to keep streets and public areas clean to avoid pollution and the spreading of diseases during the whole year. Lastly, this institution requires to provide smart services through its smart city platform which is being deployed.

- Waste management company

It needs to provide its services in a cost-efficient way, lower its GHG emissions and make use of the newly deployed bins equipped with level sensors. Furthermore, it needs to provide its services even when problematic weather events occur by coordinating with the Snow Cleaning company schedules.

- Collection truck drivers

  They need to be informed in a user-friendly way and well in advance about schedule changes due to weather events to avoid unnecessary trips in blocked streets that are too dangerous for the collection vehicle to move in.

- Citizens

  They require to have their household waste removed frequently enough to avoid overfilled and smelly bins. In addition, they need to be informed of any schedule change due to weather events, so that they can take the trash bins out at the suitable time.

1.2.3 Sustainability Aspects

The sustainability of a system is tightly connected to its ability to continue to exist and function in the long term as circumstances evolve; it is not only related to the environmental aspect but also it needs to take in consideration societal and individual well-being, economic prosperity and the long term viability of its technical infrastructure [5]. To conduct a sustainability analysis for our proposed solution, first, it was identified to which Sustainable Development Goals (SDG) of the 2030 Agenda [21] it is related to (see figure 1.1). Afterwards the expected effects / outcomes were mapped into the 5 sustainability dimensions identified in [5], namely the individual, social, economic, technical and environmental dimension. The framework presented in [22] served as a tool to gain more insights in the chains-of-effects that our system presents throughout the whole sustainability spectrum.

According to What a Waste report [7] on a global scale, waste management processes are responsible for 5% of total global *GHG emissions* , affecting climate change. Except that, solid waste is the largest source of *pollution in oceans* causing irreversible marine life damage and pollution. On a regional scale improper waste collection and disposal has an immediate effect on public *health* and *environmental degradation*. These statements

Figure 1.1: Sustainable Development Goals affected by inadequate waste collection.

are to show the magnitude of the negative effects of improper waste handling. This thesis work does not reverse these figures and facts but it rather contributes with potential improvements towards more sustainable operations in this domain. An in-depth sustainability analysis is presented in section 5.3.

1.3 Research Questions and Objectives

Given the above background and motivation we identify the following research questions:

1. **How can we build a reasoning model for proactive adaptation of behavior? What are the most common characteristics of currently deployed IoT-enabled waste management solutions?**

   To answer this question the state-of-the-art will be investigated regarding proactive adaptation of behavior, methods for reasoning in pervasive systems, as well as the currently employed methods in IoT enabled waste management.

2. **How can we build and validate a system to enable proactive adaptation of behavior in the waste management scenario?**

   To achieve this, a system behavior, reasoning model, and architecture that incorporates the proposed reasoning model will be defined. A system prototype will be implemented, efficiency metrics for the reasoning model will be proposed and the results will be analyzed.

1.4 Research Contribution

This thesis work makes the following research contribution:

1. A system architecture and a reasoning model named ProAdaWM is designed based on: state-of-the-art work for proactive adaptation; limitations of the IoT-enabled waste management solutions; and on identified requirements for sustainable waste disposal.

2. ProAdaWM system prototype is implemented and evaluated for several use cases based on information provided by the municipality of Skellefteå.

3. The conference paper with the main aspects and outcomes of this research was accepted in the 12th ruSMART conference.

1.5 Research Methodology

For choosing a suitable research methodology we were based on the type of our research questions and objectives. The Design Science Research Methodology (DSRM) [2] is a research methodology that incorporates Design Science (DS) principles in Information Systems (IS) applied research discipline (see figure 1.2).

Since, in the scope of this thesis, theoretical tools are studied and evaluated to create an artifact, a reasoning model, DSRM is a suitable fit. The objectives of the present research are mapped with the selected methodology's steps as follows:

1. **Identify Problem and Motivate.** Study methods of Proactive Adaptation of Behavior, IoT-enabled waste management solutions; identify possible gap and formulate research problem.

2. **Define Objectives of a Solution.** Define the desired behavior adaptation for the proposed solution.

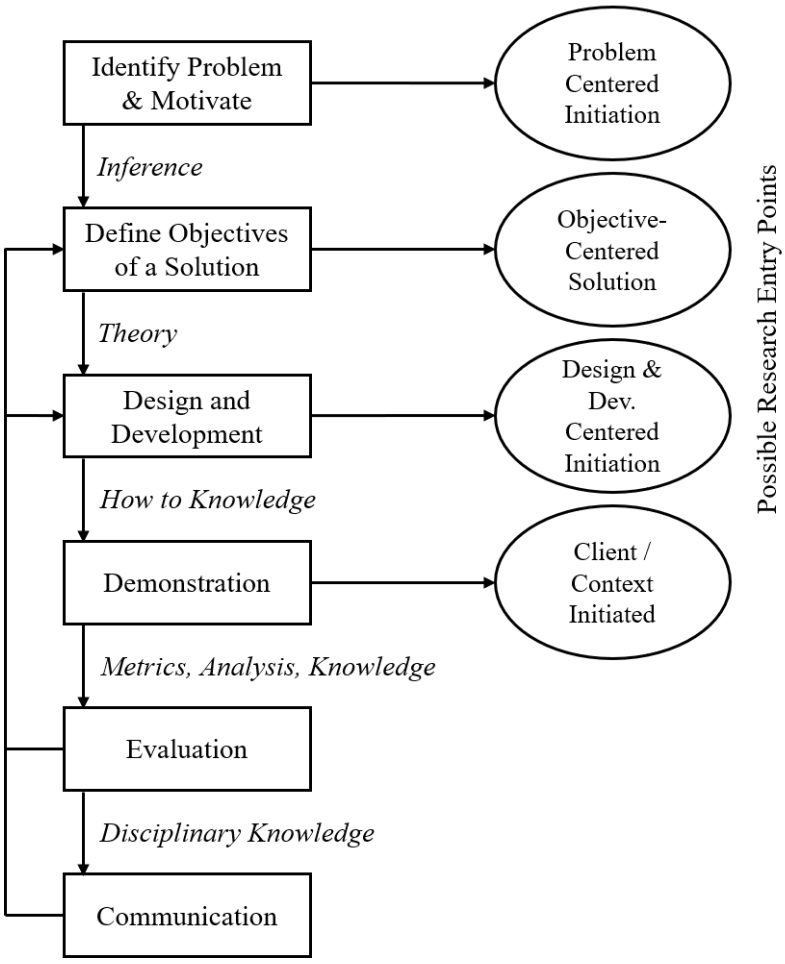


Figure 1.2: Design Science Research Methodology [2].

3. **Design and Development.** Build the ProAdaWM reasoning model for proactive adaptation of behavior. Specify system prototype scope and requirements; specify system prototype architecture.

4. **Demonstration.** Present the proposed solution to stakeholders.

5. **Evaluation.** Implement a system prototype and evaluate the reasoning model through a case study. Define metrics and test the ProAdaWM reasoning algorithm on several use cases in the smart waste management scenario.

6. **Communication.** Write and submit a conference paper.

1.6 Research Scope and Delimitation

The research presented in this thesis provides a generic reasoning model and system architecture in the scope of IoT for the waste management problem in smart cities. It assumes the existence of smart bins deployed throughout the city and connected via an IoT platform.

The model validation is carried out through a case study with realistic configurations and assumed data. No real sensor data is considered as input for the model creation and validation, since data collection is not in this work's objectives.

1.7 Thesis Outline

Chapter 2 presents the literature review and existing works regarding proactive adaptation of behavior and IoT-enabled waste management.

Chapter 3 describes the behavior of the proposed system, as well as the theoretical basis of ProAdaWM reasoning model.

In chapter 4 it is proposed a system architecture which depicts the main components and communications between them.

Chapter 5 gives the main system prototype implementation details and the validation results for the reasoning model.

Chapter 6 summarizes this thesis work by presenting the conclusions and potential future work.

2 Background and Related Work

The first chapter introduced the scope of this thesis work, its research questions and objectives. The current chapter presents the state-of-the-art regarding IoT and smart connected devices, proactive adaptation of behavior, reasoning methods for pervasive systems and IoT-enabled waste management solutions.

2.1 IoT and Smart Connected Devices

The term IoT was first used by Kevin Ashton in 1999 to illustrate the power of connecting radio-frequency identification (RFID) tags utilized in corporate supply chains to the Internet for counting and tracking goods without the human intervention, in other words, it describes a system in which sensors can be a means of connecting physical objects to the Internet [23]. In *Recommendation ITU-T Y.2060, Overview of the Internet of things* [3] ITU-T gives the following definitions for the Internet of Things and related concepts:

Definition 2.1 ***Internet of Things****: "A global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies." [3]*

Definition 2.2 ***Device****: "With regard to the Internet of things, this is a piece of equipment with the mandatory capabilities of communication and the optional capabilities of sensing, actuation, data capture, data storage and data processing." [3]*

Definition 2.3 ***Thing****: "With regard to the Internet of things, this is an object of the physical world (physical things) or the information world (virtual things), which is capable of being identified and integrated into communication networks." [3]*

Sánchez López et al. [24] in their definition of an architecture framework for Smart Object systems define a *Smart Object* as an object that possesses a unique identity; can sense and store sensor measurements associated with them; is able to make its identification,

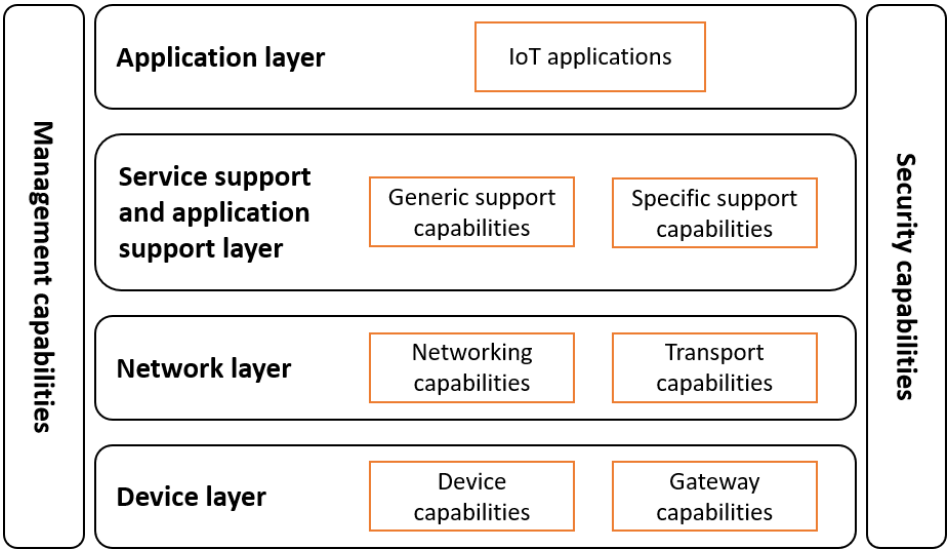


Figure 2.1: IoT reference model [3].

measurements and other attributes known to external entities such are other objects or systems. Moreover, the authors add that a smart object should make decisions about themselves and their interactions with external entities.

Given the definitions presented above, it can be said that a *Smart Object* is a *device* equipped *thing*, able to take decisions about itself and its interactions. For instance, a normal plastic trash bin can be turned into a smart object when:

1. It is equipped with a sensor that measures its physical characteristics (temperature, pressure, fill level etc.).
2. It is uniquely identifiable, RFID tags can be utilized for this.
3. It is connected and identifiable in a network.
4. It can capture and process data, for example, the smart bin notifies another entity of the system when a threshold fill level has been reached.

There is no strictly defined IoT architecture and many versions are proposed in the related research and industry fields. For example, Microsoft, IBM and AWS propose their own

conceptual architecture models with different layers and components [25, 26, 27]. For this reason, in this section is presented only the IoT reference model as recommended by ITU-T [3], this is a general model that conceptually encompasses the widely used architecture models in industry. This reference model (see figure 2.1) consists of the following layers:

- **Application layer**. It contains IoT applications.
- **Service support and application support layer**. This layer consists of two capability groupings, namely the generic support capabilities (data processing or data storage), and the specific support capabilities which are particular capabilities tailored for the requirements of different IoT applications.
- **Network layer**. The networking capabilities provide control functions such as network access, mobility management, authentication and authorization. The transport capabilities provide connectivity for the IoT service and application specific data information.
- **Device layer**. It provides capabilities for handling interaction with the communication network, ad-hoc networking, sleeping and waking up; as well as gateway capabilities that consist of supporting devices connected through different kinds of technologies.
- **Management capabilities**. This layer includes functionalities such as device management, diagnostics, firmware or software updating; local network topology and traffic management. In addition it can also offer capabilities for application-specific requirements.
- **Security capabilities**. The security capabilities should be present at any layer and handle authorization, authentication, data confidentiality and integrity protection.

2.2 Proactive Computing

The term "Proactive Computing" emerged at a time when sensors and actuators were starting to proliferate and embedded processors were enabling Ubiquitous Computing. Want et al. [28] extended Tennenhouse's definition of a proactive system by adding the capabilities to anticipate future events by being context aware and applying statistical

reasoning; ability to give real time support by relying in the evolving wireless sensor networks and high processing power.

In [4] the authors define proactivity as the ability to mitigate or eliminate undesired future events or to identify and take advantage of future opportunities. They introduce a basic model for proactive event driven computing, by dealing with prediction of future events based on current events, and reacting before these events occur in order to mitigate unwanted effects. To take optimal decisions based on the goal of the system, they use the notion of occurrence probability and cost of an event. Their model satisfies the pattern "detect - forecast - decide - act" as shown in figure 2.2. The phases of detection and forecast have been extensively researched. However, regarding the decision and acting phase based on proactive principles most of the systems have a reactive nature, meaning they act to events after they have happened [29].

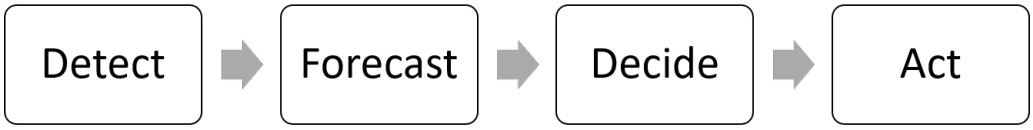


Figure 2.2: Pattern of a proactive event-driven model as described in [4].

In [30] it is proposed a framework that provides automatic proactive adaptation of behavior in pervasive environments based on the predefined utility and cost function of the adaptation. The solution aims to get all the possible real-time configurations of an application in an appropriate time. The framework relies on one context prediction management component which provides subscriptions to context information and prediction. Secondly, the configuration management component is responsible for finding all the possible valid configurations for the application based on the predicted context. Next, the valid configurations are rated based on their utility to cost ratio and an adaption alternative is chosen and forwarded to the context-aware application component which executes it.

Differently form the aforementioned paper, in [31] the user configures manually not only the cost function to undesired events and to the alternative actions but also the prior probability of it. In this solution the authors use Bayesian Networks to calculate the cost risk

functions based on the causal relationships between the contextual elements and their respective probabilities. The online decision making is triggered by the prediction of an undesired event and its associated context. Based on the cost risk function provided by the Bayesian Network the framework suggests the optimal action accompanied with the optimal time for its implementation utilizing an optimized Bellman equation. A key component of this solution is the sensor feedback which monitors the cost evolution after a decision has been made and updates the cost risk functions for the next decision process. The approach is validated in a manufacturing scenario in the area of oil and gas industry and demonstrates significant optimization of the cost regarding the maintenance strategy compared to the scenarios where context was not taken into account.

The authors extend the previous work in [32] where they model the decision model as a Markov Decision Process. The model recommends proactively the optimal action and the optimal time for applying it. In addition they apply Expected Loss Rate optimization and Joint Expected Losses optimization for the recommendation of the optimal times for a set of actions. As in the previous work, the user adds domain knowledge like action cost functions or cost of undesired events. They evaluate the solution in several industrial use-cases and conclude that proactive recommendations lead to optimized results in terms of maintenance cost savings, however they observe that their approach is highly sensitive to the input parameters.

In [33] the framework provides a solution for solving mutual dependencies by treating the problem as a reinforcement learning task for pervasive environments. The proposed architecture accepts some user input which is later on translated into exact goals for pervasive systems in terms of context and timing. The Adaptation module takes as input the context and goals and outputs prediction results and sequence of actions for the actuators.

The authors in [4] add to their model a proactive agent, which except receiving events as input, it is also equipped with decision logic consisting of either predetermined decision trees, or capabilities to solve a multi-objective optimization in highly dynamic environments. The basic components of the model are the Future Event, Predictive Pattern, Probability of Occurrence; Mitigating Actions; Cost and Rewards. The system has to answer the question regarding what optimal decision to take and when to take it, hence they model it as a Markov Decision Process. The solution is compared against two other policies, taking no action and taking the action with immediate highest utility and showed

substantial cost reductions.

Proactive computing models are widely present in literature with two main recurring notions, namely, predicting future context and making optimal decisions for the system based on the prediction. In the observed work, probabilistic models such as Bayesian Networks dominate when it comes to event reasoning and prediction. Such method is suitable in the case of missing or incomplete data. However, more methods can be applied to predicting context such as Sequence Predictors, Markov Models, ARMA, Kalman Filters, Branch Predictors and Neural Networks [34, 35].

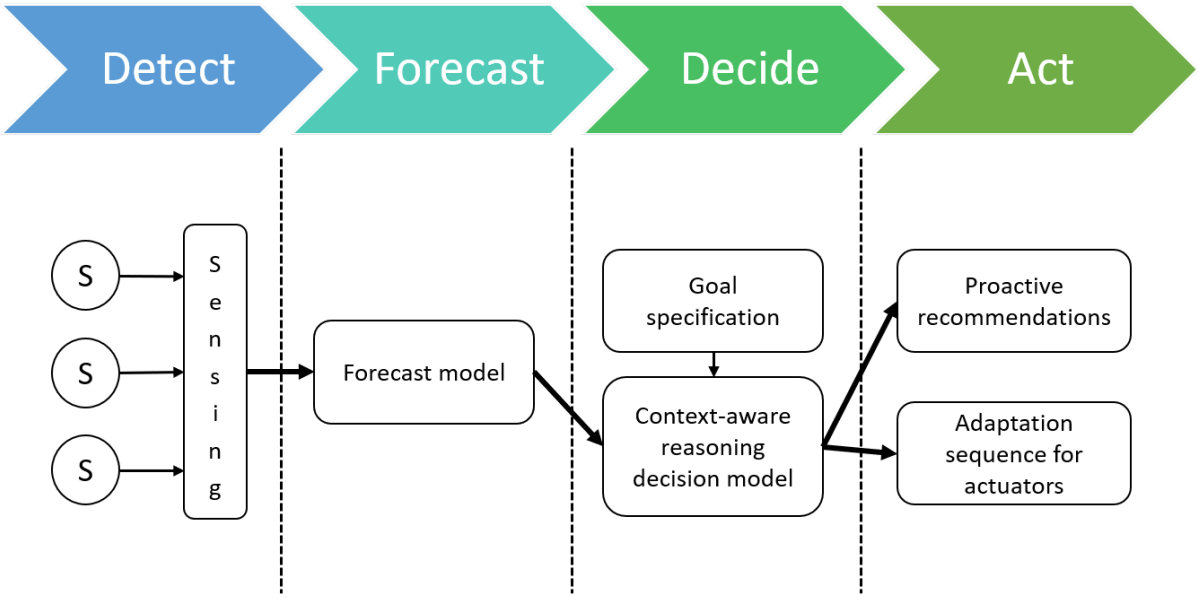


Figure 2.3: Conceptual representation of a proactively adapting system.

Figure 2.3 depicts how each phase of the the proactive pattern is achieved. As observed in the literature, there is no standard way to treat the decision phase of proactive systems. Most of the works consider cost and utility of the decision as an important metric to be the input of some decision task. Markov Decision Process is widely used for modeling the decision component. Another characteristic of such systems is that they operate in highly dynamic environments and have to adapt in real-time. Decision parameters are updated with the income of new events or feedback from previous actions. Some models are equipped with acting capabilities whereas others remain at the level of giving the user proactive recommendations. Table 2.1 categorizes relevant context-aware proactive works.

Table 2.1: Categorization of related work for proactive adaptation.

Publication	Use-case	Decision method	Prediction	Historical context	Expert knowledge	User preferences	Feedback
[33]		Reinforcement learning	Y	Y	Y	-	Y s
[30]		Cost Utility functions	Y	N	Y	Y	N
[36]	Medical Emergency Care	Rule based	Y Probabilistic Model	Y	Y	-	N
[31]	Oil and gas industry	Cost Utility functions	Y Bayesian Network; real-time	Y	Y	-	Y s
[32]	Condition-based maintenance	Markov Decision Process	Y Hierarchical Markovian Model	N	Y	-	Y s
[4]		Markov Decision Process	Y Probabilistic Model	N	Y	-	N
[37]	User recommendations	Decision Tree	N	Y ad	Y	Y	Y u
[38]	Lighting system in Smart Homes	Adaptive Fuzzy Control	N	Y ad	Y	N	Y s

[Y] Yes, [N] No
[Y s] Yes via sensor, [Y u] Yes via user, [Y ad] Yes after deployment.

2.3 Context Awareness

As stated in section 2.2 a system that proactively adapts its behavior should be aware of events that are occurring or about to occur and act accordingly, this capability is also referred as being context-aware. To further explain features of a context-aware system the basic context definitions are given:

Definition 2.4 *"**Context** is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves." [39]*

Definition 2.5 *"A system is **context-aware** if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task." [39]*

In [40] the authors define 3 levels of interactivity for context-aware applications. Interactivity is related to the user's participation in receiving the services from the application. **Personalization**: the users specify manually their preferences on how the system should behave in specific situations, for example employees can set to receive an alarm for smart bins that cross a certain threshold level. **Passive context-awareness**: remains in the level of presenting updated context information to the users, for example employees can always view the current levels of the smart bins, and decide to empty the most critical ones. **Active context-awareness**: the application autonomously changes the system behavior based on the sensed context, for example if the bins would be equipped with actuators in their lids, the lid would be automatically locked once the bin is full. In their study [40] the authors asses and conclude that users prefer active and passive context aware features in their applications as long as the application has a high usefulness, even though they might feel a lack of control. Different levels of interactivity are observed in the literature presented in section 2.2. Even though the systems' behavior changes automatically (active context-awareness), an initial domain expert knowledge or user preferences (personalization) is necessary to launch the application. Afterwards the preferences might be updated autonomously by sensor feedback.

There are several surveys concerning context-aware computing that focus on setting out

a conceptual layered architecture for context-aware systems in the domain of pervasive computing. [41] specifically present the state-of-the-art, challenges and applicability of context-aware computing paradigms and concepts in the IoT domain. The authors in the former survey present context life cycle as a cycle with 4 phases (see figure 2.4).

Context-aware applications in the IoT domain asses whether there is any change in the context of their entities, either users or smart connected objects, and decide to adapt if it is necessary depending on the application's goals. This process requires the application to be equipped with reasoning capabilities, hence a proper reasoning model. Reasoning over context data in pervasive systems can be carried out with several methods either statistical or of the artificial intelligence field. Each method has its advantages and disadvantages, hence hybrid models are used to obtain higher reasoning accuracy [41, 42, 43]. Through the reasoning process knowledge can be extracted either by *detecting* the occurring situation, or *predicting* situations to come. These methods can be applied in all stages of the data life cycle, for example a pattern recognition algorithm can be applied to raw sensor data or more complex reasoning, with ontologies for example can be applied to annotated aggregated context.

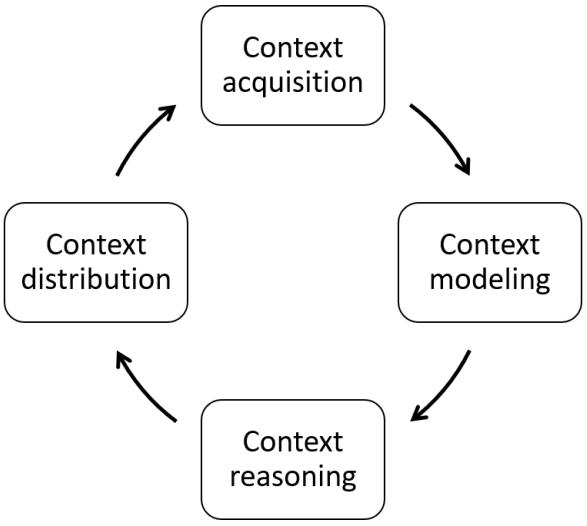


Figure 2.4: Context life cycle.

2.3.1 Reasoning Models and Techniques

A reasoning model contains the knowledge input that is necessary for an *intelligent agent* to perform reasoning. [44] identifies two main approaches for building a reasoning model:

1. **Specification-based**: also referred as the knowledge-based approach, it is the suitable approach when large data sets are not available. It can be understood and interpreted by humans, but on the other hand it requires high knowledge engineering effort as well as domain expert knowledge.

2. **Learning-based**: also referred as the data-driven approach, it is based on machine learning and data mining algorithms. This approach can be applied when large training sets and expertise is available for modeling a problem. It allows to detect dependencies in the problem domain that were not known before and can easily adapt with new incoming data. However, training of the model is resource intensive and some algorithms outcomes are not interpretable.

The most common reasoning techniques originate from the field of artificial intelligence. In this survey [41] the authors classify these techniques in 6 groups as follows:

- **Supervised learning**

  The *intelligent agent* learns a function that maps a set of inputs into an output by observing examples. The examples, labeled data, constitute the training set on which the model is learnt. Supervised learning has a plethora of methods with mathematical and statistical basis like decision trees, artificial neural networks, support vector machines etc. [45]. However, these methods require extensive data sets for higher accuracy. In addition to that, they can be resource intensive to train and validate.

- **Unsupervised learning**

  The aim is to learn patterns in the input dataset without labels. The most common form is clustering inputs based on similar features or anomaly detection. When unsupervised learning methods are applied, usually the expected outcomes of the model are not specified [41].

- **Rules**

  Rules are statements in the form IF-THEN-ELSE that encode user preferences for adaptation. In pervasive systems they offer the benefits of fast reasoning; they are suitable for resource-restricted systems and easy to implement [46]. However, as rule sets are extended, conflicts between rules might arise and as a consequence rules have to be "tweaked" manually [45].

- **Fuzzy logic**

  Fuzzy logic control is a method for reasoning in control systems in which the mapping between real-valued input and output parameters is represented by through membership functions and fuzzy rules [45]. This approach allows the use of natural language and has been used vastly in Smart Home use cases [38, 47]. It has the same drawbacks as rule-based reasoning since the rules are defined manually.

- **Ontology based**

  Ontology based reasoning is used when context is presented with semantic web languages. It has low computational complexity, however, it cannot be used as a standalone method in context-aware applications since it cannot deal with missing or ambiguous information [48].

- **Probabilistic reasoning**

  Allows representation of knowledge through graph structures which model dependencies, relations and behaviors of the input variables. The general structure is called Beyesian Network, however in literature it also appears in the form of Naive Bayes (with independence assumption of its input variables) and as Hidden Markov Models (a special case of Dynamic Bayesian Network) [45].

2.4 Smart Waste Management

Section 2.1 presented the basic definitions of IoT and smart objects, this section presents the current literature and existing work on how IoT enables WM in smart cities.

There has been substantial work regarding smart waste management solutions enabled by IoT, they mostly tackle the monitoring, scheduling and routing phase. Many works conclude that dynamic planning of the waste resources highly reduces the costs and increases

the quality and sustainability of such services by optimizing the collection frequency, location and number of containers [49, 50].

[51] proposes a taxonomy for the main characteristics of waste management models. The authors divide it in three main categories, regarding physical infrastructure, IoT technologies and software analytics. The later will be the focus of the models presented in this section. Based on this taxonomy, software analytics components might include a Decision Support System, a Geographic Information System (GIS) , a scheduling and routing model. In this brief overview of papers we will focus on features regarding the type of context included in the decision model, the decision methods for the planning of waste management processes and the adaptability of the model in highly dynamic scenarios.

GIS, in conjunction with Global Positioning System (GPS) and RFID data is an integrated part of the decision support system when it comes to managing the collection processes and the monitoring of containers [52, 51]. GIS is a powerful tool for analyzing, representing and interacting with spatial information in a fast and effective way, it is usually extended to handle even additional tasks such as routing by considering sustainability metrics [53, 54].

Among the decision methods utilized to obtain cost-saving, environmentally-aware routing and scheduling solutions in the waste management use-case, heuristic models are the most prevalent ones, since other methods such as the exact solution of a Vehicle Routing Problem, Markov Decision Processes, Stochastic Dynamic Programming have a high computational cost due to the high dimensionality of the problem [55, 19]. The difference between heuristic methods and metaheuristics is that the former is a problem specific method, whereas the latter is problem (use-case) independent.

A heuristic is presented by [19] with the objective of minimizing the covered distance, the number of vehicles and the environmental impact of waste collection based on real time data. The real time data gives information about the fill level of the bins and vehicles and the position of the latter. Their model includes two configurable parameters such as the oversize risk parameter and the optimal replenishment parameter and creates optimized short term routes. They validate the proposed model via simulation and conduct parameter analysis for the optimal bins replenishment level.

The authors in [56] extend present a cost effective dynamic routing algorithm. Simulations were run to explore the cost efficiency for two types of scenarios: one that incorporates high capacity trucks and one that does not. It is concluded that the scenario with heterogeneous trucks is more efficient regarding operational costs. The novelty of this model lies in its ability to deal with failures or emergencies in real-time by allowing rerouting.

In [55] it is introduced a parametric heuristic for solving the Inventory Routing Problem with many customers taking into account the uncertainty of the demand of collection and the long-term consequences of the decisions regarding dynamic waste collection. They build cost functions based on three components namely transportation, handling and penalties for uncollected waste based on historic data. Re-planning may occur during the day when the desired expectations are not met. To tune the model with the best input parameters on the long run, they use optimal learning techniques in an offline setting. Offline setting is suitable when cost measurements in real-time are either unavailable or expensive. The optimal parameter settings will change over time with the changing of the collection network characteristics and other external parameters such as weather conditions or holidays.

A model that focuses in the reduction of pollutants emission and operational costs is presented in [50]. Besides traveled distance and time, fuel consumption is explicitly considered as an optimization criteria. Their model considers a distinctive fill-up rate for each separate bin which is proved to be more relevant than mean values. A sensitivity analysis is conducted to understand the impact of the waste distribution on the costs and pollutant emissions. It is observed that an incrementally decreasing load leads to more pollutants emissions due to increased fuel consumption. Routing optimization in this work was carried out with GIS libraries with the metaheuristic Tabu Search technique.

To summarize, from the presented work regarding IoT-enabled WM there are several points of relevance that are utilized in our proposed model. Firstly, we are motivated by the assumption that a distinctive bin fill-up rate is more relevant than average values [50]; in our use case this value can be obtained from level sensors. Moreover, the identified need for changing model parameters during different weather events [55], reconfirms that that these systems should be enhanced with additional capabilities to cope with this specific problem. Our work is not a replacement for the aforementioned models, but rather an

extension to them. Next, commercial solutions are analyzed and compared regarding their features and reported use-cases.

2.4.1 Commercial Solutions

The previous part of this section showed some the most prominent scientific work in the field of smart waste management, focusing especially in their reasoning and decision parameters. Nevertheless it is also important to have a full picture on the applicability of such systems in real world scenarios to further validate that such systems are feasible and yield the desired results. For this reason table 2.2 presents a summary of the technologies, features and reported efficiency of the commercial solutions. All the reviewed Smart Waste Management Services providers utilize a cloud based architecture for their platform. In addition they report their improvement of the service with detailed use-cases of the cities that have adopted their solutions.

2.5 Summary

This chapter presented some of the most relevant works related to proactive adaptation of behavior. The works were categorized to identify common features and possible methods that can be applied in the scope of this thesis. Most of the works included the notion of predicted context, as an enabler for proactive adaptation and made use of probabilistic models for reasoning and forecast. In the reviewed work the decision phase was mostly tackled by utilizing utility functions given by domain experts, or by introducing user preferences. In addition to that, a categorization of the reasoning methods with their advantages and disadvantages was presented. Lastly, this chapter presented and overview of both scientific publications and commercial solutions present in the smart waste management field. The focus was on identifying the utilized tools and technologies of such systems, their decision models and how effective they are to provide environmentally aware solutions. Furthermore, we observe if such systems proactively adapt when faced with unexpected events.

Table 2.2: Commercial solutions' features.

	Architecture	Software Features	Sensor Types	Reported Improvement	Notification	Dynamic Optimized Routing	Waste Generation Prediction	Powered by	Compacting Bins
BigBelly [57]	Cloud	Cost management	Capacity	80% less collections; 75% less collection costs;	E	Y	N	S	Y
Enevo [58]	Cloud	Cost management; Analytics;	Capacity	50% reduction in collection trucks; 22% reduction in bins	-	Y	N	B	N
Compology [59]	Cloud; LTE;	Cost management	Camera; GPS; Tilt;	-	P	Y	N	B	N
Ecube Labs [60]	Cloud	Cost management; Predictive Analytics; Optimized bin location;	Capacity; GPS; Temperature; Tilt;	up to 50% reduction of waste collection costs	-	Y	Y	S	Y
Nord Sense [20]	Cloud	Cost management; Optimized bin location; Contextual awareness during navigation; Predictive Analytics;	Capacity; Temprea-ture; GPS;	80% decrease in overflowing trash cans	A	Y	Y	B	N

[A] App, [P] Phone sms, [E] E-mail
[Y] Yes, [N] No, [S] Solar power, [B] Battery

3 ProAdaWM Reasoning Model

In this chapter, it is introduced the ProAdaWM reasoning model for achieving proactive adaptation of behavior in the waste management use case. Initially, the overall adaptation behavior is described. Afterwards, a context model that will enable the desired behavior is presented. Finally, section 3.3 presents the theoretical methods on which the reasoning model is based, how they are applied in the selected scenario, as well as the overall reasoning algorithm.

3.1 Introduction

To provide proactive adaptation of its connected devices, the ProAdaWM system should be able to reason about undesired future weather events and the impact that they might have on the waste removal processes. This reasoning eventually affects the decision for adaptation. However, to take an effective and efficient decision, the system should be aware of its' users' goals.

The main objective is to reason upon advancing the collection day before the weather event occurs or not. Visiting a certain bin for emptying it well in advance, when the streets are certainly suitable for access, means that the trip of the vehicle was not wasted. However the bins might not be as full as in the normal scheduled day, hence more fuel and time is consumed to collect less waste. On the other hand, sending the vehicle for collection in the predefined day, in which a heavy snowfall is forecast to occur, poses the risk of that vehicle not being able to access some bins. The consequences of such event mean a wasted trip for the vehicle and risk for overflown bins, to name a few. The reasoning module, named **ProAdaWM** , is responsible to determine the system's behavior in this case. To achieve that, the module utilizes decision theory by conducting probabilistic reasoning and computing the expected utility (EU).

The expected behavior is depicted through the flowchart in figure 3.2. The process starts with assessing the weather conditions, performing the reasoning, and it is concluded with notifying a routing engine if any collection should be anticipated. The routing engine contains a necessary module for optimal routing based on the city topology and bins' net-

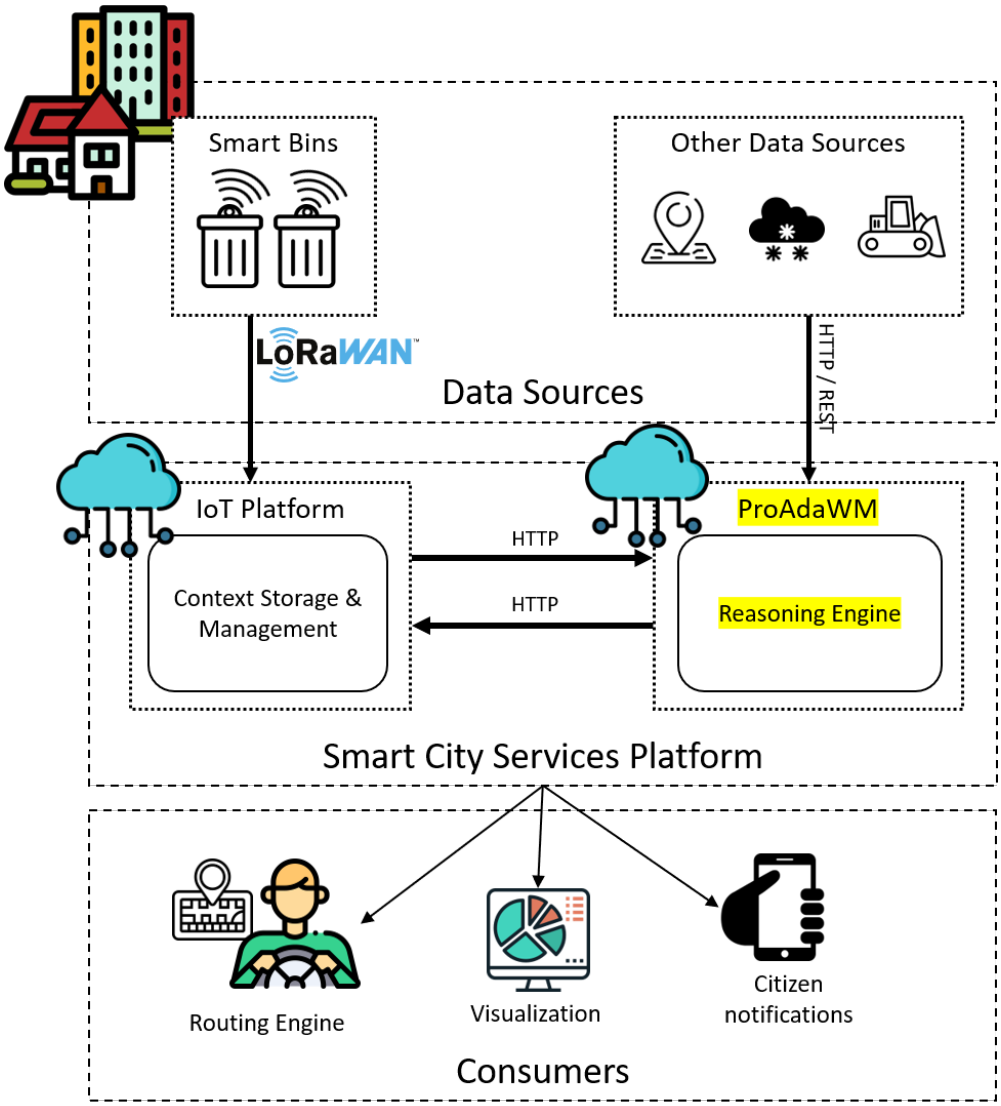


Figure 3.1: Smart WM Concept.

work. In any case its recommended routes should be confirmed by the drivers. Figure 3.1 illustrates the ProAdaWM concept, the smart devices it is connected to, and the services it offers to the consumers.

The connected devices

- Smart Waste Bins

  This is one of the core connected objects of the system. As presented in the literature review, waste bins can be equipped with level, weight, pressure, temperature, chemical and humidity sensors [51]. In this architecture is assumed that every bin has at least a level sensor incorporated and an RFID tag to uniquely identify it and connect it to its owner.

- Smart Collection Vehicle

  In the current work it is supposed that these vehicles, owned by the waste management company are equipped with a navigator. The latter has the role of informing the driver in real time about any schedule or route change. Such vehicle model is already available in commercial solutions [20, 59]. The driver should have the possibility to approve or reject a recommended route.

- Citizens' Smart Phone

  Currently, to the best of our knowledge, citizens are notified for any change on the collection day for their household waste either via the municipality website or mailing lists. However these are usually late notifications, after the collection truck has failed to empty the bins. In the proposed system architecture citizens are informed in a faster and more reliable way such as SMS or push notifications on their smart phones.

- Weather API

  To be able to reason upon upcoming weather events, the system needs to obtain data regarding current weather observations, forecasts and alerts. Such information can be provided by Open Data API-s. For example in Sweden free API-s are available at the Swedish Meteorological and Hydrological Institute website. Alternatively more customized forecasts and alerts can be obtained by commercial weather services.

- Snow Cleaning Company API

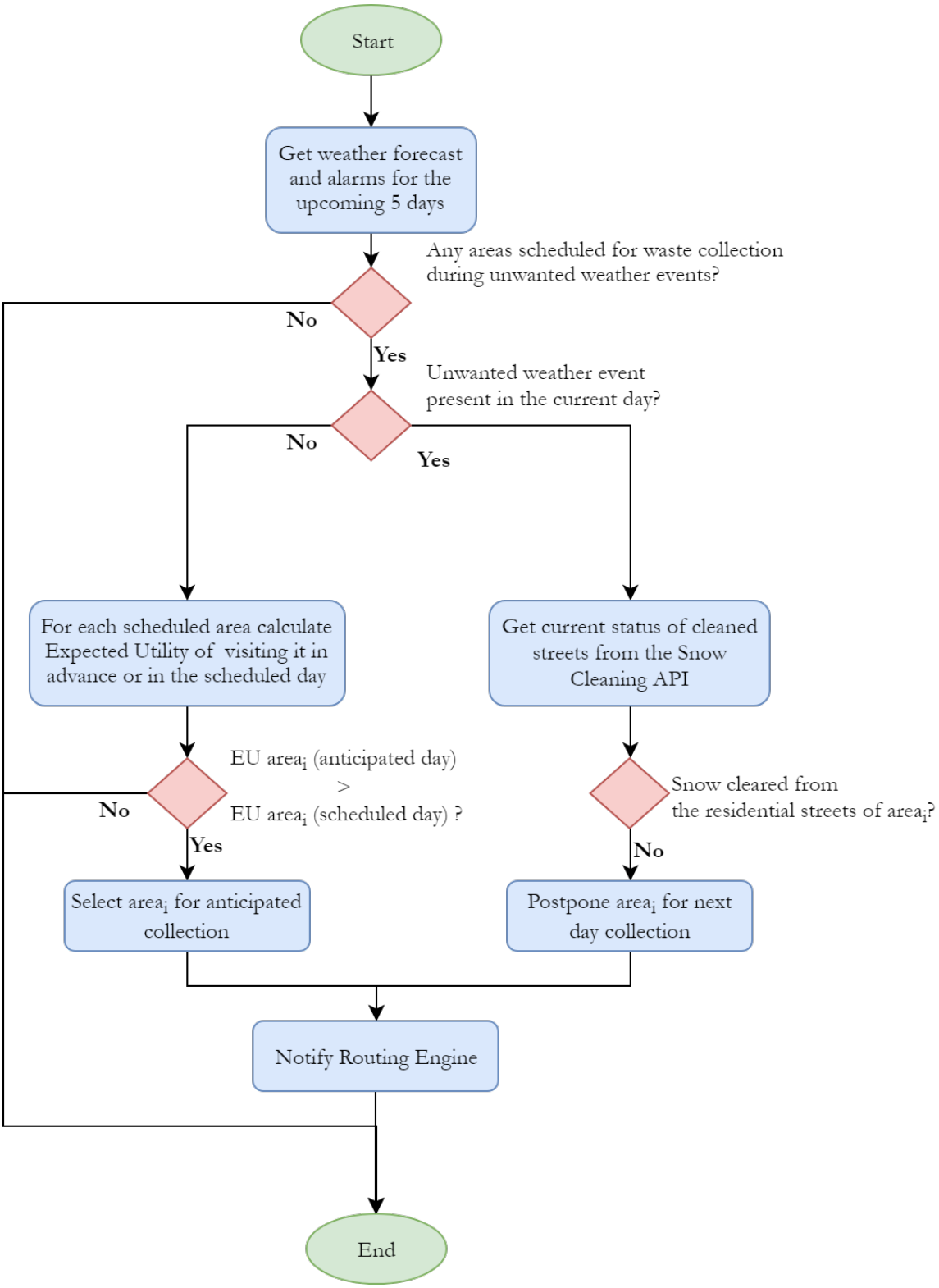


Figure 3.2: System behavior.

As observed from municipalities' reports, waste collection operations during severe winter weather events are highly dependent on the state of the streets, specifically if they have been cleaned by the snow plow machines or not. Hence it is important to coordinate the schedules of both the waste management and snow management company. However, while doing so, consideration should be put to the fact that snow cleaning process duration cannot be estimated with full precision. For example, the service might take longer in reality due to heavy traffic or other physical conditions of the road and weather.

- Maps API

  Spatial information is necessary for determining the bin location, and the road network.

3.2 Context Model

To enable the aforementioned behavioral adaptation for the connected devices, a context model is necessary to represent the entities involved in the scenario and their attributes. The remainder of this section explains the selected entities in detail.

- Weather: necessary data consists of weather precipitation forecasts up to one week ahead. A greater forecast horizon is not suitable since the reliability of the forecast is expected to be lower[1]. In addition to that, weather warnings regarding ice and snowfall are considered in the model.

- Area: comprises a physical area with accessible streets whose waste bins are emptied at the same day through a predefined schedule.

- Segment: a street within an Area characterized by the same features throughout its whole length. Depending on their street type, and the traffic flow they support, segments have different cleaning priorities from the Snow Cleaning Company. For example, primary streets crucial for the traffic might have a high priority, secondary streets and important routes for schools or hospitals are served next, whereas other residential streets are the last ones to be cleaned in case of snow.

[1] https://scijinks.gov/forecast-reliability/

- Smart Bin: placed near households or in specific designated areas if they are shared between businesses or many households. They are characterized by their current waste level, the maximum volume of waste that they can support as well was the waste type. A bin belongs to an Area, to a Segment and to a user.
- User: is characterized by the location of its household, hence it is associated with an Area and Segment. In addition, information about their phone number and e-mail are used for notification purposes in case of schedule change of the waste collection.

Table 3.1 presents the context entities, their attributes and possible value ranges in detail.

3.3 Reasoning Model

If the Reasoning Engine of ProAdaWM were to know with certainty the future state of the entities on which the adaptation decision depends, then the adaptation task would be straight forward. However, in the real world, certainty for a future event happening is never 100%, neither are the outcomes of taking an action. Given this, the model should be capable to reason only with the set of data that are made available to it, and under this incomplete information determine which action would be more beneficial. The former implies that the system is aware of its goals and the degree of utility or "satisfaction" it gets from a certain outcome of its actions. The current section gives the definitions of the theoretical concepts and methods utilized to model the adaptation for our use case.

Algorithm 1 presents the overall reasoning process. A Bayesian Network (BN) is used to model the reasoning about the street conditions (referred as segment in the proposed context model) based on weather events and other parameters. The proposed network should answer the question: *What is the probability that a segment is in suitable conditions to be accessed by the collection vehicle?* This question can be extended if more evidence is available, for instance *What is the probability [...] when an ice alert has been issued?*

The next step is computing the expected utilities based on the several outcomes of taking the action, where action is defined as "visiting a segment in a day D". Possible outcomes are emptying the trash bins if the segment is safe to be accessed or leaving the waste untouched until it is collected in a subsequent date. Both these outcomes have different

Table 3.1: Context Model.

Attribute	Value Type	Possible values	Unit
Weather			
warnings	JSON object	{type: 'warning_type', duration: {start_date: 'Y-m-d', end_date: 'Y-m-d'}}	
precipitation	String	[0; $+\infty$)	mm
Area			
segmentCount	Integer	{0, 1, $+\infty$}	
binCount	Integer	{0, 1, $+\infty$}	
collectionUtility	Integer	[0; 100]	
wasteCollectionPriority	Integer	{1, 2, 3}, where 1 is high and 3 is low	
schedulePeriod	Integer	{0, 1, $+\infty$}	days
scheduleValidity	timestamp range	[startDate; endDate]	
Segment			
binCount	Integer	{0, 1, $+\infty$}	
steepness	String	[0%; 100%]	
snowCleaningPriority	String	{1, 2, 3}, where 1 is high and 3 is low	
wasteGenerationRate	Float	[0; inf)	kg/day
collectionUtility	Float	[0; 100]	
areaID	Integer	{0, 1, $+\infty$}	
Smart Bin			
location	String	(latitude; longitude)	
volume	Float	[0; maximumCapacity]	liter
wasteType	String	Organic; General;	
maximumCapacity	Integer	140; 190; 660;	liter
segmentID	Integer	{0, 1, $+\infty$}	
areaID	Integer	{0, 1, $+\infty$}	
uniqueID	String		
User			
userID	Integer	{0, 1, $+\infty$}	
segmentID	Integer	{0, 1, $+\infty$}	
email	String		
phone	String		
preferredContactMethod	String	{ 'sms', 'email', 'app' }	

Table 3.2: List of Notations.

Notation	Meaning
b	A smart bin
s	A Segment
a	An Area
w	Waste Amount
cw	Current Waste Amount
ew	Expected Waste Amount
l	Current Level
$maxL$	Maximum Level, for bins
$maxC$	Maximum Capacity (volume)
$r_{s,t}$	Waste generation rate for a segment in a specific time of the year
t_{sch}	Scheduled collection day
t_0	Current day
U_s	Segment Utility
U_a	Area Utility
EU_s	Segment Expected Utility
EU_a	Area Expected Utility
sa_s	Suitable Access for Segment
k_s	Weight Coefficient for Segment
S_a	Number of segments for area a
B_s	Number of bins for segment s

utilities. To mimic the behavior of a rational agent, we can say that leaving the waste untouched has less utility than collecting it. The utility functions will be explained in detail in section 3.3.2.

After computing the expected utilities for the two different days, the day when reasoning is taking place and the normal scheduled day, the system decides which action to take based on the greatest expected utility.

3.3.1 Bayesian Network for Street Accessibility

Bayesian Networks are powerful graphical models for dealing with uncertainty; they can be built by using quantitative and qualitative modeling, since empirical observed probabilities can be integrated with subjective probabilities provided by domain experts [61]. The

Algorithm 1: ProAdaWM Reasoning Algorithm

Data: $currDate$, $affectedAreas$, $weatherEvent$
Result: $selectedAreas$

initialize empty array for $selectedAreas$;
foreach a *in* $affectedAreas$ **do**
  EU_{a,t_0}, $EU_{a,t_{sch}}$ = 0;
  get $segments_a$, $maxC_a$;
  foreach s *in* $segments_a$ **do**
    get $maxC_s$;
    k_s = $maxC_s$ / $maxC_a$;
    $P_s(sa_s = true)$, $P_s(sa_s = false)$ = calculateSuitableAccessProbabilities(s, $weatherEvent$);
    cw_s, ew_s = calculateWasteAmounts(s, $currDate$, $scheduledDate_a$, $genRate_s$);
    EU_{s,t_0} = computeUtility(cw_s, $maxC_s$);
    $EU_{s,t_{sch}}$ = computeUtility(ew_s, $maxC_s$);
    EU_{a,t_0} = EU_{a,t_0} + k_s * $currU_s$;
    $EU_{a,t_{sch}}$ = $EU_{a,t_{sch}}$ + k_s *$expU_s$;
  end
  if $EU_{a,t_0} > EU_{a,t_{sch}}$ **then**
    add a to $selectedAreas$;
  end
  return $selectedAreas$;
end

main definitions concerning a BN (also referred as a belief network or causal network) are given below:

Definition 3.1 *A **Bayesian Network** is a directed acyclic graph (DAG) where each node represents a random variable, discrete or continuous, and is annotated with quantitative probability information. Nodes are connected by a set of arrows representing relationships between them. If an arrow is directed from X to Y, X is defined to be the parent of Y. Each node X_i contains the conditional probability distribution $\boldsymbol{P}(X_i|Parents(X_i))$ that quantifies the effect of the parent nodes on it [45].*

Definition 3.2 *An **entry** in the **joint probability distribution** represents the probability of*

the conjunction of specific values of its variables and it's value is given by the formula:

$$P(x_1, ..., x_n) = \prod_{i=1}^{n} P(x_i | parents(X_i)) \tag{3.1}$$

The conditional probability distribution of a node is also called Conditional Probability Table (CPT). A directed arrow means that the parent has a direct influence on the child, usually, and in the scope of this thesis, the direction of the arrow determines a causal relationship, so in figure 3.3 random variables X_i cause Y.

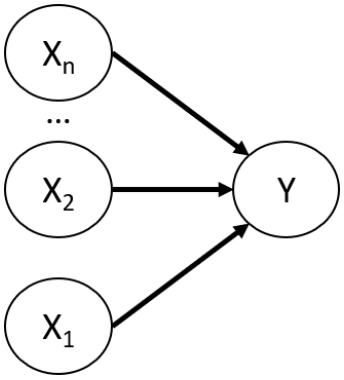


Figure 3.3: Causal relationship between network nodes.

A variety of methods exist for constructing a BN. Traditionally they have been built by knowledge engineers in collaboration with domain experts, whereas recently these models are derived by high level specifications or learned by data sets [62]. Within the scope of this thesis work we will focus on expert elicited BN-s. Querying a BN with or without any available evidence will output the probability of the target node being in one of its defined states. However that information does not say much if reasoning for adaptation needs to be tackled. For this reason, the model can be extended with the notions of action and utilities, to provide an effective tool for decision making under uncertainty. The formalism is called **influence diagram** or **decision network**. The lack of a proper data-set to characterize our problem, is one of the main reasons for not utilizing approaches based on supervised or unsupervised learning that would require extensive amounts of data for learning the model and obtaining the segment probabilities. On the other hand, more basic approaches such as rule based or fuzzy logic, do not offer any well defined theoretical extension to handle decision making under uncertainty.

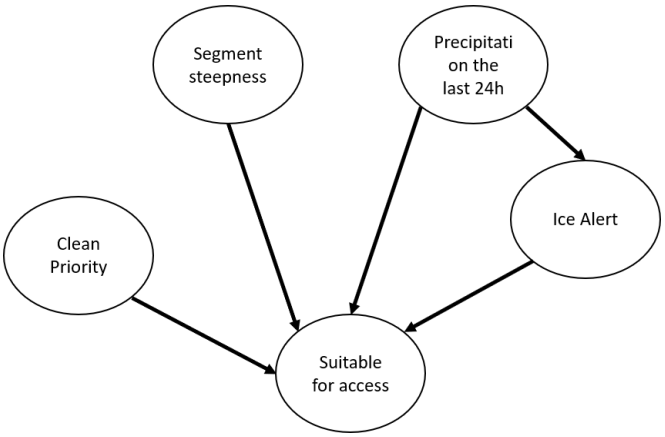


Figure 3.4: Network topology.

The response towards severe or harsh weather differs form city to city based on their infrastructure and preparedness for the event. For example, snow storms can have a much negative impact in a city where it rarely snows compared to a city where snowfall is more frequent. In the case, where complete granular historical data is not available, and the nature of the problem differs based on location, expert knowledge is essential for deciding how the system should adapt. The BN proposed hereby (figure 3.4) for determining the probability of a street segment to be suitable for access by the waste collection vehicle, is therefore a structural model, non-instantiated completely with real world probability values. This section aims to identify the most relevant factors in any city use-case.

Parameter selection

To select the most suitable parameters that affect the problem of street accessibility a three step process was followed:

1. An interview was conducted with Skellefteå municipality where the main causes for problematic street accessibility for waste collection vehicles were identified.
2. Other online municipalities' reports and notices were observed for any disruptions in their waste collection process due to weather events.
3. Current literature regarding factors that impact the road conditions and national weather services websites were consulted.

The selected parameters for the BN are justified below:

- **Clean Priority**

  Cleaning priority refers to the priority that the snow clearing company has assigned to a specific street. Many sources indicate that the cleaning process takes place in phases [63, 64], where primary and secondary roads are cleared first and only afterwards the residential streets and neighborhoods. This is a relevant variable in the proposed BN since the majority of the residential bins, are indeed in residential areas. The collection trucks require suitable conditions to start and stop the vehicle very frequently, an aspect that can compromise the driver's and citizens' safety or cause property damage if the road is not cleared properly [14, 65].

  In our model we consider three priority levels, namely "Level 1" which refers to the primary roads such as highways or crucial arteries in the city; "Level 2" secondary streets, which might usually be two-lanes streets; and "Level 3", the lowest cleaning priority corresponding to the residential streets.

  Streets of different priorities are characterized by different traffic fluxes. The latter is proven to have an immediate effect on the road conditions, causing increased road temperatures in lanes with heavier traffic [66].

- **Street Inclination**

  Operating a heavy vehicle such as the waste collection truck, varying between 25 tonnes to 35 tonnes, is a risky task during severe weather events especially as the road inclination increases [2]. As described in the context model, each segment is characterized by its inclination based on the levels described in table 3.3.

Table 3.3: Slope characterization as adapted from [6].

Value	Description
0-9%	Little to gentle slope
10-30%	Moderate to steep slope
>30%	Extremely to excessively steep slopes

- **Precipitation the last 12 hours and Ice Alert**

  According to United Kingdom's national weather service [3] snowfall can quickly lead to impacts on road networks, ranging from longer journey times to complete

[2] http://icyroadsafety.com/tips.shtml
[3] https://www.metoffice.gov.uk/weather/guides/severe-weather-advice#Snow

disruptions of road services. It can influence the visibility distance, pavement friction and lane obstruction, and as a consequence increase the vehicle crash risk [67]. Another problematic event that can cause transport disruptions is the presence of ice or slush in the street. These aspects are present in the reports for waste collection processes disruption [14, 15, 16, 17, 18, 65] in several municipalities.

Modeling the road surface conditions and forecasting them constitutes a difficult task due to many involved processes such as freezing rain, hoar frost, freezing surface water, or freezing fog [68]. The scope of the proposed BN is not to model the problem of road conditions forecast, but if it is suitable to be visited by a heavy collection vehicle, based on expert knowledge.

For ease of construction of the BN and elicitation of the posterior probabilities three snow precipitation levels are considered, whereas the "Ice Alert" can take yes / no value as shown in table 3.4. The snow precipitation levels in mm use the Snow Water Equivalent (SWE) measurement; it can be considered as the depth of water that would result if the snow amount would be melted instantaneously [4]. Ice alerts are usually issued no sooner than 48h, hence, if the BN is queried for a time later than 48h ahead, the Ice Warning parameter will not be given a value in the query. In that case the posterior probability is obtained with the following query: $P(SuitableAccess = true|CleanPriority = Level1, SnowPrecipitation = s0_5, StreetSteepness = little_to_gentle)$.

The snow precipitation levels should reflect the impact that they have in the street accessibility, for example up to 5mm of snowfall should have a less negative impact than the level from 5 to 20mm, which is in fact the range of snow when usually the snow cleaning company starts to clear the streets.

Table 3.4: Parameter values for snow precipitation and ice warning.

Parameter notation	**Value**	**Description**
SnowPrecipitation	s0_5	From 0 to 5 mm of snow precipitation in the last 24h
	s5_20	From 5 to 20 mm of snow precipitation in the last 12h
	s20_inf	More than 20 mm of snow precipitation in the last 12h
	none	No snow precipitation in the last 12h
IceWarning	Yes	Ice warning has been issued
	No	No ice warning has been issued

[4] https://www.nrcs.usda.gov/wps/portal/nrcs/detail/or/snow/?cid=nrcs142p2_046155

Querying the BN explained above will yield a probability value that a segment will be suitable for access under certain weather conditions; that probability value is utilized to compute the expected utility for visiting that specific segment as explained in the following section.

3.3.2 Utility Functions for Waste Collection

A **utility function** $U(s)$ is used to represent the intelligent agent's preferences and goals. It gives the degree of satisfaction for being in a state s. The expected utility of an action a given the evidence, $EU(a|e)$, is the average utility value of the outcomes, weighted by the probability that the outcome takes place [45]:

$$EU(a|e) = \sum_{s'} P(RESULT(a) = s'|a, e) * U(s') \tag{3.2}$$

where s' is the outcome state of taking action a.

The principle of **Maximum Expected Utility** (MEU) states that a rational agent picks the action that maximizes its expected utility [45].

Before constructing a utility function for a decision making problem, there should be a clear view on the goals of the "intelligent agent". As stated in chapter 3, our reasoning model aims to avoid unsuccessful trips of the collection vehicle, and avoid overflown bins. Given this, the utility, which represents the satisfaction degree, is directly dependent on the amount of collected or uncollected waste in an area or segment. Negative utility values express dissatisfaction.

$$cw_s = \sum_{b=1}^{B_s} (l_b \div maxL_b) * maxC_b \tag{3.3}$$

$$ew_s = cw_s + r_{s,t_0} * (t_{sch} - t_0) \tag{3.4}$$

Equations 3.3 and 3.4 show respectively how the current and expected waste amount is computed for a segment. They both depend on the current waste level in the smart bins. Waste generation patterns vary depending on seasons, holidays, demographic and economic factors [13, 8]. It is assumed here that the generation rate will be specific for a segment, to capture patterns depending on social and demographic factors, as well as specific for a certain time of the year, to capture characteristics that depend on seasons or holidays. For instance, there might be a higher generation rate during Christmas holidays.

As a rational agent would decide, more collected waste represents a higher utility for visiting the segment for collection, whereas more uncollected waste signifies higher dissatisfaction. The latter is represented with negative values in the proposed equation 3.5. The model considers as uncollected waste, the amount of waste present in an inaccessible segment ($sa_s = false$).

However, lower and upper bounds are necessary. Suppose the model computes the following future segment state: the expected amount of waste in the whole segment is more than this segment's capacity to hold waste ($w_s > maxC_s$). In this case it is not desired for the utility to be more than 100, otherwise the agent would always choose to postpone the collection.

$$U(w_s, maxC_s, sa_s) = \begin{cases} min(\frac{w_s}{maxC_s} * 100, 100) & \text{if } sa_s = True \\ -1 * min(\frac{w_s - maxC_s}{maxC_s} * 100, 100) & \text{if } sa_s = False \end{cases} \tag{3.5}$$

$$EU_{s,t_0} = U(cw_s, maxC_s, True) \tag{3.6}$$

$$EU_{s,t_{sch}} = P(sa_s|true) * U(ew_s, maxC_s) + P(sa_s|false) * U(ew_s, maxC_s) \tag{3.7}$$

The uncertainty factor in our model is related with the state of a segment to be suitable for access by the collection vehicle or not. The latter is introduced in the expected utility

formula (equation 3.7) by the following: $P(sa_s)$ and its value is inferred by the proposed Bayesian Network in section 3.3.1. In equation 3.6 there is no probability factor, due to the assumption that for the current day, in which we are planning the new possible schedule we are certain that all the segments of the area are accessible.

The decision on which action to choose, whether advance the collection before the hindering event, or conduct the waste collection at its normal scheduled day, is determined based on MEU, maximizing the expected utility. This decision proposed until now is efficient and straight forward in the case when the expected utilities for all the segments of an area are higher at the same day, it means the whole area can be rescheduled for collection at the same point in time.

However, the system should be able to decide in an area basis, and not schedule segments separately. For this reason, it is introduced the concept of an area score. The score can be regarded as an overall utility for visiting an area for collection at a certain point in time; it is the weighted sum of the expected utilities for each segment in the desired area, where the weight of each segment is proportional to its maximum waste capacity and the sum of all weights equals 1. Equations 3.8 and 3.9 represent how the whole area score is computed. Equation 3.10 shows how the segment weight is computed.

$$Score_{a,t_0} = \sum_{s=1}^{S_a} EU_{s,t_0} * k_s \tag{3.8}$$

$$Score_{a,t_{sch}} = \sum_{s=1}^{S_a} EU_{s,t_{sch}} * k_s \tag{3.9}$$

$$k_s = \frac{maxC_s}{maxC_a} \tag{3.10}$$

3.4 Summary

This chapter presented the expected ProAdaWM system behavior, as well as the context model which represents all the involved entities that take part in the adaptation. The reasoning methods and parameters are explained and justified. Adaptation decisions are taken based on probabilistic reasoning and utility theory. Having introduced the theoretical basis, the next step is to design a system architecture that enables such adaptation.

4 ProAdaWM Architecture

Chapter 3 focused on the theoretical basis at the core of the reasoning model and the system behavior. This chapter presents a system architecture, its main components, their functionalities and the communication sequence between them.

4.1 Introduction

This section presents the technical architecture of the ProAdaWM system (figure 4.1). Its aim is to identify how the components are related, what communications take place between them, the possible data sources and the web services made available to the user. The remainder of this section explains each component in detail.

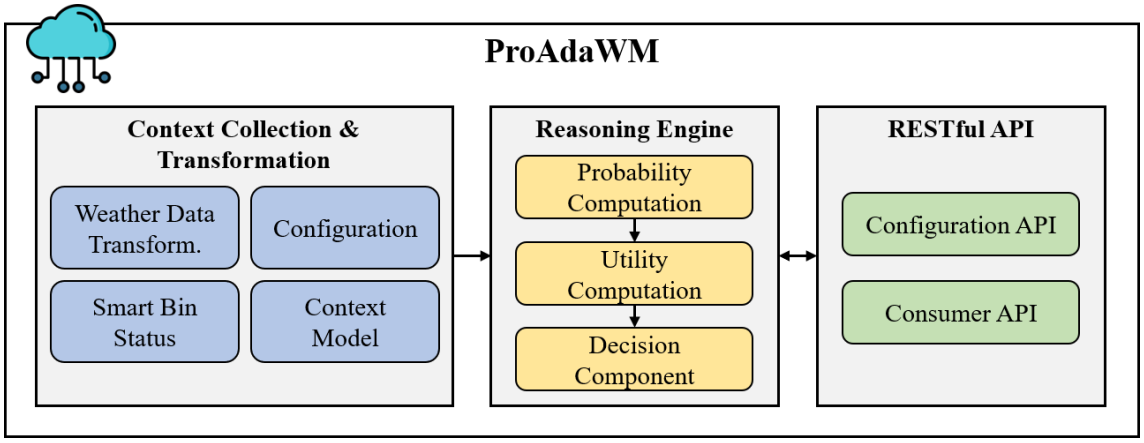


Figure 4.1: ProAdaWM architecture and system components.

ProAdaWM Module

The main aim of our proposed system is to provide proactive waste collection related recommendations to the connected devices, by reasoning on the weather information, the area setting and the current level of its bins. To allow this the ProAdaWM module should be capable of accepting real time data from the respective sources, conduct the reasoning,

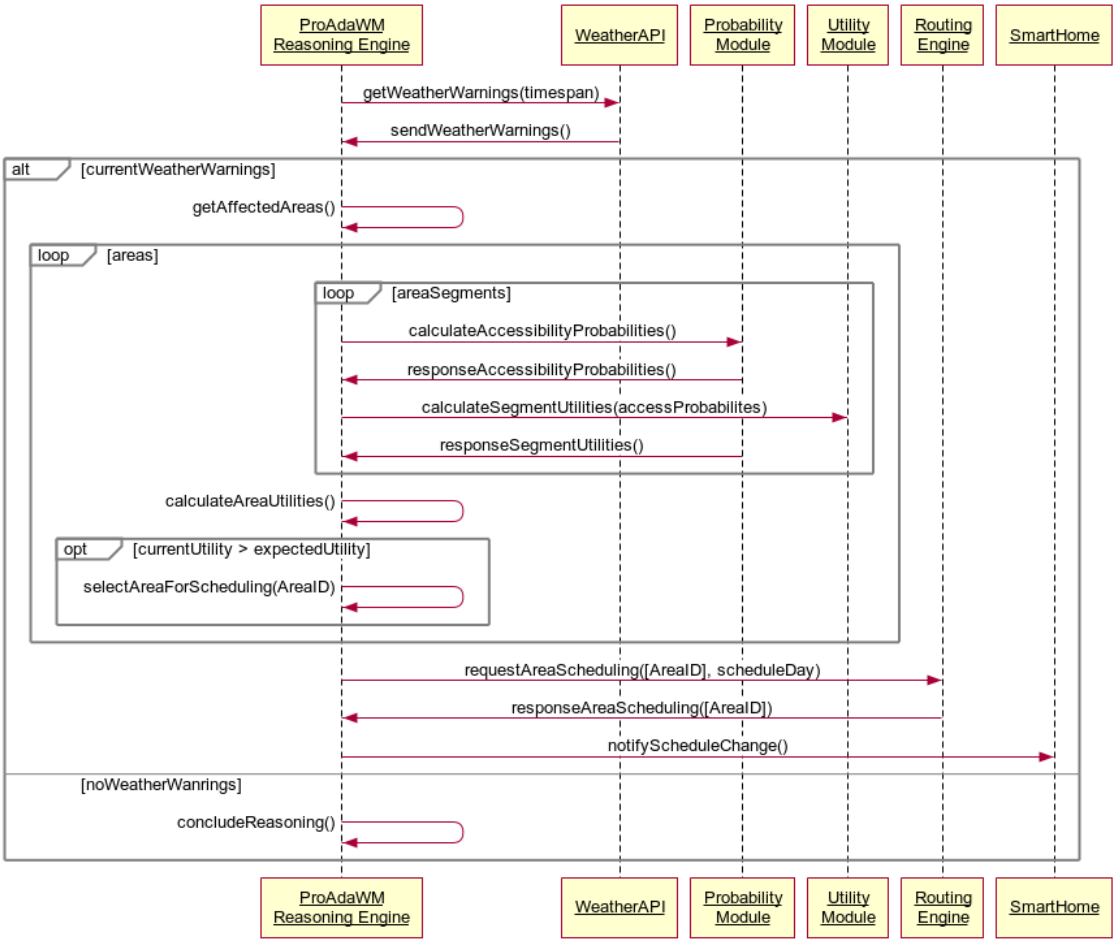


Figure 4.2: Sequence diagram of the communications between the ProAdaWM components and external components.

and provide the reasoning result to the respective consumers.

In the conceptual architecture (figure 3.1), ProAdaWM is depicted as an independent module that can be integrated to any IoT platform, to provide Smart City Services. In our solution, we propose a completely detached module architecture, in the sense that it uses standard communication protocols with external components in order to increase it's reusability. Communication with the IoT platform, open data sources and the consumers is carried out through REST API-s via the HTTP protocol.

To allow the previously mentioned communications, the module is provided as a cloud -based application, hence it requires a web server for the data exchange. The choice of the technologies to implement the web server is free and up to the developer, as long

as it fulfills the required functionalities, hence the technologies for our scenario will be explained in chapter 5.

4.2 Context Collection and Transformation

The reasoning capability of ProAdaWM highly depends on the context it collects from its connected devices, the weather open data and the snow cleaning company. The *Context Collection and Transformation* module transforms this data in the right format to be passed as an input to the reasoning core.

- Smart Connected Devices Data

  This subcomponent is responsible for fetching the state of the smart bins deployed in the city from the IoT platform. The communication is conducted with HTTP/REST requests. Since the received data represents sensor readings from an IoT infrastructure, there is the risk of missing or erroneous data, hence the component should offer support for these cases.

- Weather Open Data

  This subcomponent is responsible for fetching and transforming the necessary weather information. There are plenty weather open data providers, usually these can be offered by government agencies and each of them offers the data in a different format and in different units.

- Snow Cleaning Company API

  This subcomponent is utilized when there are scheduled waste collections and when snow cleaning from the streets is happening at the same day. It is utilized to fetch the status of cleaned streets or areas.

Configurations

To make available the reasoning capabilities of the module in a whole city level, it is essential to configure its areas, segments, and the placement of the smart bins in a proper

manner, which best describes these entities. In addition to that, several reasoning parameters regarding the weather events or waste generation rates, need to be stored viewed and edited whenever it is necessary. For instance, the user (employee of the waste management company) configures which "Ice Alert" level to be taken in consideration from the reasoning model. For this reason the a "Configurations" component is necessary. It should offer the option for persistent data storage as well as a set of API-s to manipulate the configurations.

Context Model

The Context Model contains the blueprint of the relationships between the context entities. The proposed system utilizes Object Role Modeling [69] as a context modeling technique, it is part of the graphical modeling techniques and it offers support for capturing relationships in the context model [41]. This component should offer tools for context retrieval to the other components of the system. The contents of the context model are defined prior to deployment of the system by the developer in collaboration with the domain expert and it cannot be changed during run-time by the users.

4.3 Reasoning Engine

The *Reasoning Engine* contains the reasoning logic explained in chapter 3. It accepts as input the formatted weather information, area structure, current bin states and gives as an output recommendations on whether to advance the collection for a certain area or not. The reasoning process can either be triggered by a scheduled procedure in the module itself, or be started on demand by the *Routing Engine*. The main components of this module are as follows:

- Probability Computation: should be able to perform Bayesian Inference on a predefined Bayesian network. Specifically, it is supposed to give as an outcome the probability that a given segment, will be suitable for access under given circumstances. Querying requests are sent to this component when the requirements are met for a problematic future weather event as depicted in the sequence diagram in figure 4.2.

- Utility Computation: computes the current and expected utilities for visiting an area for collection. It requires as input the current bin levels, which are queried from the smart city platform via HTTP/REST services and the segment access probabilities which are passed form the *Probability Computation* component. This component outputs not only the aggregated area utilities but also the specific utilities for each segment, which are necessary for the decision component.

- Decision Component: responsible for sending or responding to a schedule request from the *Routing Engine* of the system, and based on its response to determine all the users that will have an advanced collection. The communication can utilize the publish / subscribe pattern. This means that the routing engine is always listening for re-schedule requests, and on their reception, it responds with the list of areas / segments that can be collected in advance. Afterwards the decision component forwards the details of the users that need to be notified to the external *Notification Module*.

4.4 Service API-s

The system makes available a set of REST API-s for several consumers or for configuration purposes. They are called with the common HTTP methods such as POST, GET, DELETE etc.. The aim of this component is to provide a friendly programming interface to further develop visualization or reporting modules.

- For consumers

  Even though notification of the routing engine and the users takes place from the *Decision Component*, there is the necessity to retrieve this information even at subsequent moments for reporting or visualization purposes. For this reason, Consumer API-s, if queried give information regarding the decision results of a certain day. For example, when a user accesses its app for the municipality services, the view that displays his new collection date, utilizes one of these API-s of the ProAdaWM module.

- For configurations

These web services are crucial for configuring the city information regarding areas, segments, their connected bins and other decision parameters. They are utilized not only when the system is initially launched, but also during its life time, for instance when an area topology is changing, or new bins are added to a specific segment.

4.5 Summary

This chapter presented the technical architecture of the ProAdaWM system. It identified the main components, their functionalities and how the communication takes place between them. In addition to that, it recommends the basic technologies and communication protocols that are best fit for this system, specifically, the cloud based architecture and communication through the HTTP protocol. However, the choice for implementing the subcomponents is up to the developers.

5 ProAdaWM Implementation and Validation

Chapters 3 and 4 presented respectively the context model along with the reasoning model, and the proposed system architecture with its main components' functionalities. This chapter gives the implementation details for the proposed architecture. Furthermore, it presents validation metrics for the reasoning model, and the obtained results for different selected use-cases.

5.1 Implementation

This section presents the specific implementation details regarding the utilized tool, technologies and data sources. The implementation serves as a validation method for the proposed system architecture.

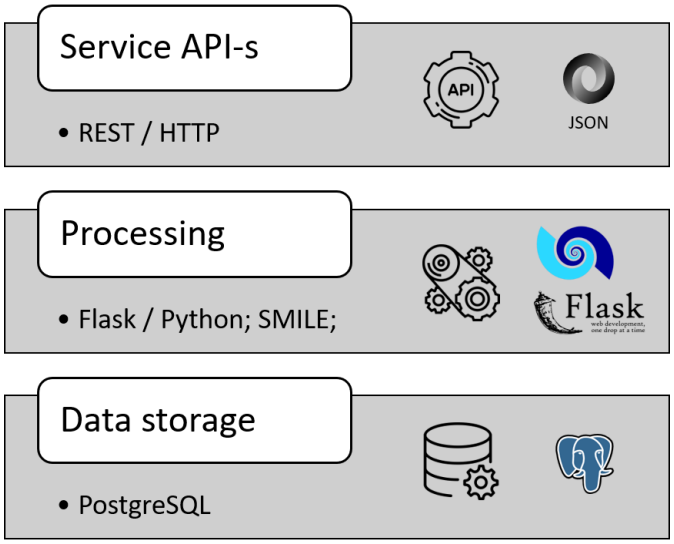


Figure 5.1: ProAdaWM System technology stack.

Figure 5.1 depicts the technology stack utilized for the ProAdaWM prototype consisting of three main layers: data storage; processing layer; and services API layer. **PostgreSQL** [5] is chosen as a database. It is an open source object-relational database system that uses and extends the SQL language, except that, it does not pose any limitations on the programming language that it can be coupled with. The data storage layer handles the

[5]https://www.postgresql.org/

storing process for the "Configurations" of the system. A non-relational database (such as MongoDB) has high support for scaling out, making it the right fit when dealing with big data. However, ProAdaWM does not handle the retrieval and storage of the sensor data from the sensor interface itself; it queries only the context it needs from the IoT platform, for this reason there is no risk for the database to grow massively due to sensor generated data. The reasoning engine needs to perform different aggregations and joins on its defined entities, relational databases are well known to be more suitable for such operations compared to non-relational ones.

The processing layer implements the logic for the reasoning model using **Python** [6] and **SMILE Wrappers** [7] for the Bayesian Network. The Services API layer exposes the web services of the ProAdaWM system to the consumers. To achieve this, a web server is necessary to accept requests. In our implementation Flask [8] (a Python microframework), is utilized for a fast and efficient development of the API-s.

5.1.1 Data Retrieval and Transformation

Section 4.2 explained the functionalities of the Context Collection and Transformation Module and identified the need for the system to be connected to a weather data source for obtaining weather related context, and to a Smart City platform in order to obtain the real-time state of the smart bins. In this section are given the details of the retrieval of these two data sources and how the data is transformed to be compliant with the proposed context model.

The weather data is obtained from Swedish Meteorological and Hydrological Institute (SMHI) [9] via their Open Data services [10]. SMHI offers real-time datasets regarding meteorological observations, forecasts, alerts etc.., for our prototype only "Meteorological Forecasts" and "Warnings" API are utilized. Both API endpoints can be queried via a location parameter, in this case the coordinates of a city within Sweden.

[6] https://www.python.org/
[7] https://support.bayesfusion.com/docs/Wrappers/
[8] http://flask.pocoo.org/docs/1.0/
[9] https://www.smhi.se/en/about-smhi
[10] http://opendata.smhi.se/apidocs/

Data transformation is essential at this point because the variables of interest to our reasoning model are not delivered at the desired format and unit. For example, the "Meteorological Forecasts" endpoint offers an hourly forecast for the first 24 hours of the forecast and then the time interval changes into 3, 6 or 12 hours. Instead, the proposed reasoning algorithm requires an aggregated precipitation value within the last 12 hours. Based on the documentation, the precipitation amount is not specific to the a single point in time, but to the whole interval, hence the precipitation amount for the desired 12 hour is a weighted summation of the mean snow precipitation level and the duration. Table 5.1 shows the relevant fields from which information is retrieved.

To find the consecutive days with snowfall the *Weather Symbol* variable is used, specifically by filtering the days with the most occurrences of the values that signify *Light, Moderate and Heavy Snowfall*. To calculate the precipitation level we are based on the *Precipitation category* and *Mean precipitation intensity* variable.

If queried, the "Warnings API" will return the warnings currently issued for the whole territory of Sweden on a region level, so there is the need to know how to filter these warnings based on the date when they are effective, the unique identifier of the region and the warning type. This functionality is also implemented in the data retrieval and transformation component.

Table 5.1: Relevant variables from the weather forecast endpoint.

Notation	Description	Unit	Values	Meaning
Wsymb2	Weather symbol		Integer, 1-27	25=Light Snowfall; 26=Moderate Snowfall; 27=Heavy Snowfall
pmean	Mean precipitation intensity	$kg/m^2/h$	Decimal	
pcat	Precipitation category		Integer, 1-6	1=Snow; 2=Snow and Rain

5.1.2 Bayesian Network Implementation

This subsection gives an overview of the chosen tools for the implementation of the BN for street accessibility, how the parameter values were determined and the network's re-

```
CALL
>>> from controllers import weather as w
>>> api = 'https://opendata-download-warnings.smhi.se
.../api/version/2/alerts.json' # define the api endpoint
>>> date = '2019-01-18' # define the date alerts are needed for
>>> region_id = '033' # Vasterbottens lan kustland
>>> event_type = 'black ice, freezing rain'
>>> w.get_weather_warnings(api, date, region_id, event_type)
```

```
Return value:
{
    "status": "success",
    "warnings": [
        {
            "effective": "2019-01-15T02:50:11+02:00",
            "expires": "2020-01-16T14:55:58+02:00",
            "type": "black ice, freezing rain",
            "severity": "Severe",
            "urgency": "Expected"
        }
    ]
}
```

Figure 5.2: Example call to the "Warnings API".

sponse in several use-cases with different hypotheses.

There are many libraries that can be utilized for implementing a Bayesian Network and conducting inference through it. For our implementation, GeNIe Modeler [11] was used as a modeling tool; it offers the advantages of a graphical interface to create, learn, and refine a network model. In addition to that it uses the SMILE Engine, which offers wrappers for building custom applications with it. Given this, once modeled, the network file can be imported in the prototype application and conduct reasoning through it. In out prototype application the SMILE Python wrappers were utilized.

For experiments and validation purposes, to assign the prior and posterior probabilities we were based on historical data, if available, and on assumptions. The *SnowPrecipitation* node prior probabilities were assigned based on average climate information for the city of Skellefteå for a timespan of 30 years [70]. To determine the probability tables for the rest of the nodes in our scenario the following assumptions were considered:

[11] https://www.bayesfusion.com/genie/

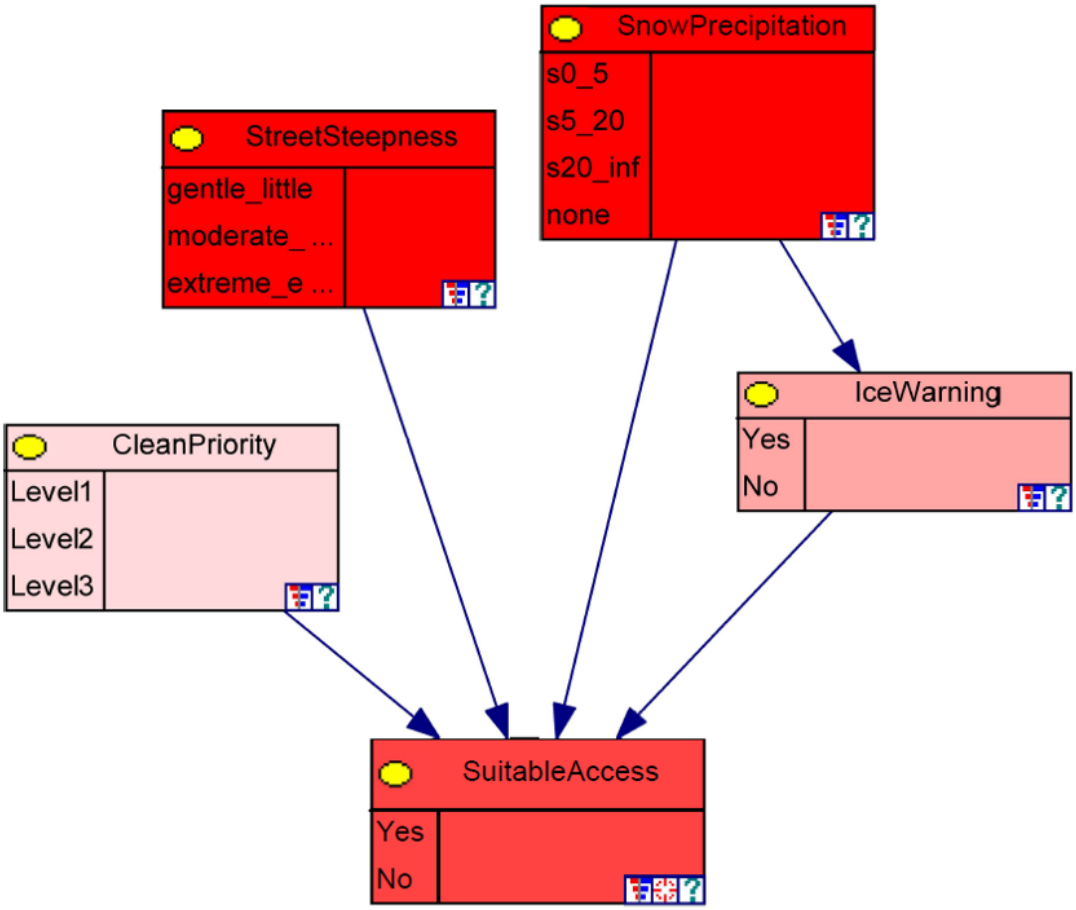


Figure 5.3: BN structure as modeled in Genie.

1. The probability that a segment is suitable for access is higher for more prioritized streets in the event of snow precipitation and ice warnings.

2. The probability that a segment is suitable for access is higher for lesser steep streets in the event of snow precipitation and ice warnings.

3. Most of the segments that the waste collection vehicle has to use are residential ones.

4. Most of the segments have gentle to little road inclination, and extreme to excessively steep segments are mostly uncommon.

5. The probability that a segment is suitable for access is higher if an ice warning has not been issued and all the other parameters are the same.

Given this, table 5.2 presents the different probabilities for $SuitableAccess = Yes$; from the best cases, suitable access probabilities close to 100%, to the worst cases, suitable access probabilities less than 40%. The latter probabilities represent the cases when the street inclination is "extreme to excessive". As it is shown in the table, suitable access probabilities go down as the precipitation levels increase.

The initial BN setup was configured with the GeNIe Modeler (figure 5.3), however that is not a viable solution in a real world scenario, since the experts are supposed to configure the suitable access probabilities. For this reason in the proposed prototype is given the possibility for the user of the system to configure custom probabilities. To achieve this, the function made available by the SMILE Python Wrappers are utilized.

It is also worth pointing out that the posterior probabilities which describe a city's response towards a weather event in the *SuitableAccess* node, are highly dependent on the

Table 5.2: BN cases.

Clean priority	**Street inclination**	**Snow precipitation forecast**	**Ice Alert**	**Suitable Access Probability**
Level 1	Little to gentle	up to 5mm	Yes	92%
Level 1	Little to gentle	up to 5mm	No	94%
Level 1	Little to gentle	5mm to 20mm	-	86%
Level 1	Little to gentle	more than 20mm	-	75%
Level 2	Little to gentle	up to 5mm	Yes	90%
Level 2	Little to gentle	up to 5mm	No	92%
Level 2	Little to gentle	5mm to 20mm	-	83%
Level 2	Little to gentle	more than 20mm	-	70%
Level 3	Little to gentle	up to 5mm	Yes	88%
Level 3	Little to gentle	up to 5mm	No	90%
Level 3	Little to gentle	5mm to 20mm	-	78%
Level 3	Little to gentle	more than 20mm	-	65%
Level 1, 2, 3	Extreme to excessive	up to 5mm	-	40%
Level 1, 2, 3	Extreme to excessive	more than 20mm	-	20%

city's characteristics and its infrastructure. For example, a city in a geographical position where snowfalls are always present during winter and has proper infrastructure, might be more prepared than a city when snowfalls occur less often. Moreover, even the minimal amount of snow precipitation that causes disruptions for the collection vehicle types can vary. Hence, the role of the domain expert or the data analyst is crucial to determine the probabilities that best describe reality. If deployed, the ProAdaWM system should initially make use of domain experts to determine its BN probabilities. Once the system is put in use, and more data is made available, the system can be extended by providing the capability to automatically tune BN parameters through learning algorithms. There are several adaptive learning algorithms for the online and offline setting as shown in [71], but they remain outside the scope of this thesis.

5.1.3 API-s

A set of initial API-s were implemented to validate the proposed system architecture. As described in section 4.4 the system makes available two groups of API endpoints, for configuration purposes, and for consumers. All API-s are documented with Swagger [12].

Endpoints for configuration purposes are responsible for reading, adding, editing, deleting areas, segments, bins and configuring reasoning parameters. Among the parameters to be configured are included the data sources or possible endpoints for notifications. In addition to that, they allow to configure custom probabilities in the BN. All the endpoints accept requests and respond in JSON format. For instance, figure 5.5 illustrates a POST HTTP request to configure the probabilities of the BN. In the request body cpt_index refers to the index that uniquely identifies a posterior probability based on the given evidence; prob refers to the new probability value to be assigned as a float; node_id refers to the node identifier as a string.

From the consumer API-s, the necessary endpoint for retrieving reasoning results was implemented as shown in figure 5.4; the call takes as input parameters the characteristics of the upcoming weather event and will conduct the reasoning on all the areas configured in the system. In addition to this, a basic Graphical User Interface (GUI) was built to demonstrate the reasoning results (figure 5.6a); conduct reasoning with a custom weather

[12] http://editor.swagger.io/

```
POST : http://127.0.0.1:5000/reason.json
Request Body :
{
 "event_type": "snow",
 "precipitation_level": "s5_20",
 "start_date": "2019-01-01",
 "end_date": "2019-01-04",
 "ice_warning": "Yes",
 "city_type": "robust"
}
Response Body:
{
    "reasoning_details": [
      {
       "area":1,
       "area_utilities":
        {
         "current_utility":72.508,
         "expected_utility":71.495
        }
      },
     ...
    ],
    "schedule_advance": [1, 4]
}
```

Figure 5.4: Example of reasoning request and response.

```
POST : http://127.0.0.1:5000/api/custom
Request Body :
{
    "cpt_index": 15,
    "prob": 0.8,
    "node_id": "SuitableAccess"
}
Response Body:
{
    "msg": "Network successfully updated!",
    "status": "success"
}
```

Figure 5.5: Example of custom probability configuration request and responses.

forecast (figure 5.6b); show the upcoming scheduled collections for the areas (figure 5.6c).

This section described the implementation details of the data retrieval module, the reasoning engine, and the API-s made vailable by the system. Moreover it described the

prototype and demonstrated that the modules are communicating and computing the decision outcome as they should. The next step in the validation process is to examine how the reasoning model performs in different use cases and compute the sustainability metrics.

5.2 Reasoning Model Validation through Case Study

This section presents the experimental setup for evaluating the ProAdaWM reasoning model. The experiments are conducted to asses how the system responds towards different weather events in different collection area settings. Synthetic and real data provided by Skellefteå Municipality are utilized. To evaluate the performance of ProAdaWM we consider the fuel consumption rate for several scenarios, with and without the utilization of the proactive reasoning.

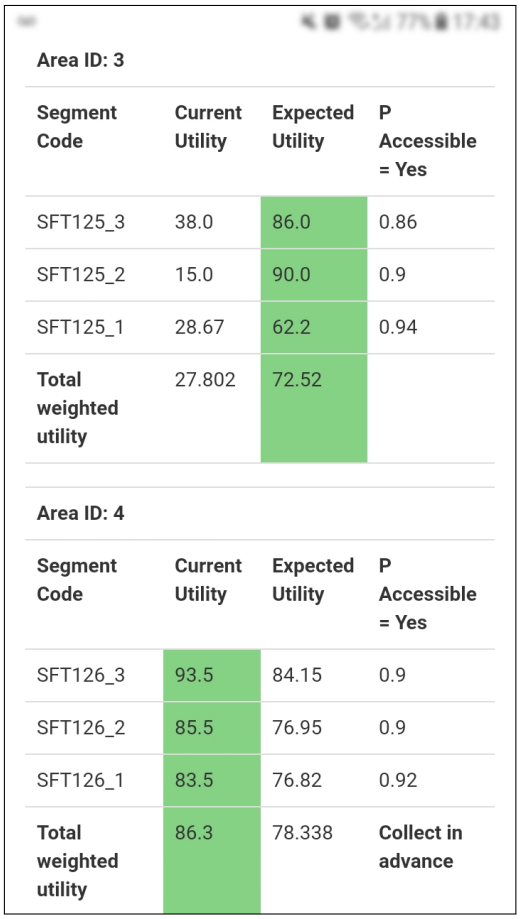
5.2.1 Scenario Modeling

Employees responsible for waste management and collection in Skellefteå Municipality were consulted not only for setting up evaluation scenarios as close as possible to the reality, but also to further validate that our system is tackling a real world problem and is compliant with the way the waste management company handles their operations. The aim of this section is to analyze how the utility for emptying the trash bins of an area evolves when faced with different unwanted weather events for different collection methods.

In addition to that, fuel consumption for the collection vehicle is considered as well. We evaluate the ratio of average consumed fuel amount per liter of collected waste (AFW) when proactive reasoning is applied, against the AFW without proactive reasoning. The latter (AFW) is calculated as shown in equation 5.1:

$$AFW = \frac{AverageFuelPerKm * RouteLength}{CollectedWasteVolume} \tag{5.1}$$

where the route length is the sum of the lengths of the accessible segments and the trip



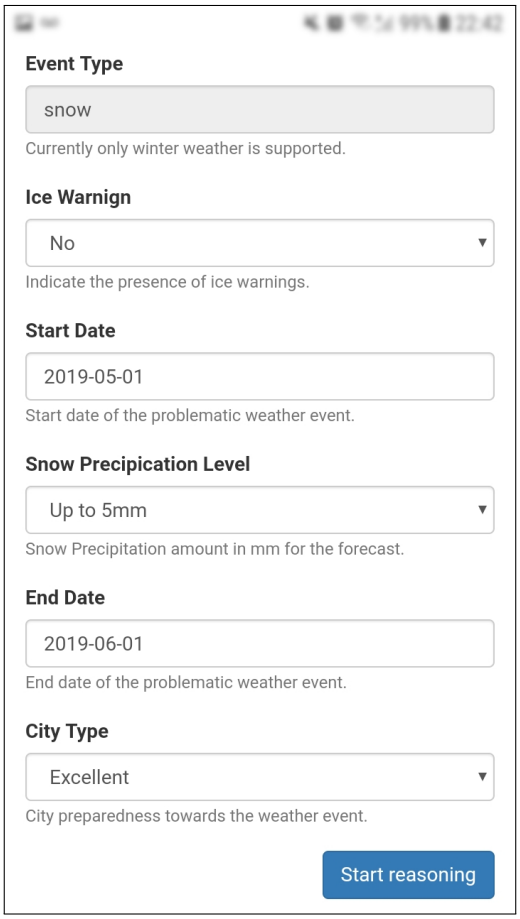
Area ID: 3

Segment Code	Current Utility	Expected Utility	P Accessible = Yes
SFT125_3	38.0	86.0	0.86
SFT125_2	15.0	90.0	0.9
SFT125_1	28.67	62.2	0.94
Total weighted utility	27.802	72.52	

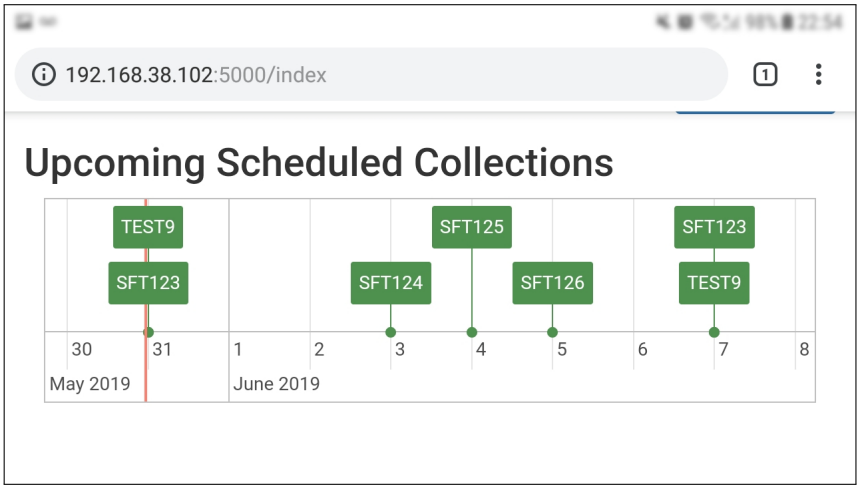
Area ID: 4

Segment Code	Current Utility	Expected Utility	P Accessible = Yes
SFT126_3	93.5	84.15	0.9
SFT126_2	85.5	76.95	0.9
SFT126_1	83.5	76.82	0.92
Total weighted utility	86.3	78.338	**Collect in advance**

(a) Reasoning results.



(b) Reasoning parameters form.



(c) Scheduled areas.

Figure 5.6: Prototype graphical interface.

from and to the collection point (equation 5.2).

$$RouteLength = 2{*}d_{CollectionPoint}{+}\sum_{s=1}^{S} l_s, \text{ where } S \text{ is the number of accessible segments.} \tag{5.2}$$

Waste compaction in the collection vehicle is not considered. Consequently, the fuel efficiency ratio (FER) is calculated as shown in equation 5.3:

$$FER = \begin{cases} \dfrac{AFW_{Advanced}}{AFW_{Static}} & \text{Reasoning result: Advance collection day} \\ \\ \dfrac{AFW_{Static}}{AFW_{Advanced}} & \text{Reasoning result: Keep the same collection day} \end{cases} \tag{5.3}$$

where $AFW_{Advanced}$ is the value of AFW in the advanced collection day, and AFW_{Static} is its value in the initially scheduled day. The $AverageFuelPerKm$ is factored out from the equation, where as the $RouteLength$ has different values depending on the number of accessible segments.

Given equation 5.3, if FER is smaller than 1 it means that a more fuel efficient collection takes place if ProAdaWM reasoning model is applied. A $FER = 0.3$ signifies that the average amount of consumed fuel to collect one liter of waste when applying the proactive reasoning algorithm is 30% of the average amount of consumed fuel to collect one liter of waste when not applying the algorithm.

Since currently no data exists for reporting inaccessible segments, the ratio is calculated for four different cases of accessible segments: when 25%, 50%, 75% and 100% of the segments will be accessible during a severe weather event within the area. The segments that will be accessible are assigned randomly and they remain with the same accessibility status for the different weather event cases. Three different weather cases are considered: snow precipitation of up to 5mm (WeC 1); from 5mm up to 20mm (WeC 2); more than 20mm (WeC 3) for the last 12 hours. It is assumed that the decision process takes place 3 days before the weather event and that no ice warning has been issued yet, hence "IceWarning" variable value for the BN will be unassigned.

Given this, we introduce the experimental setup and the test cases as follows:

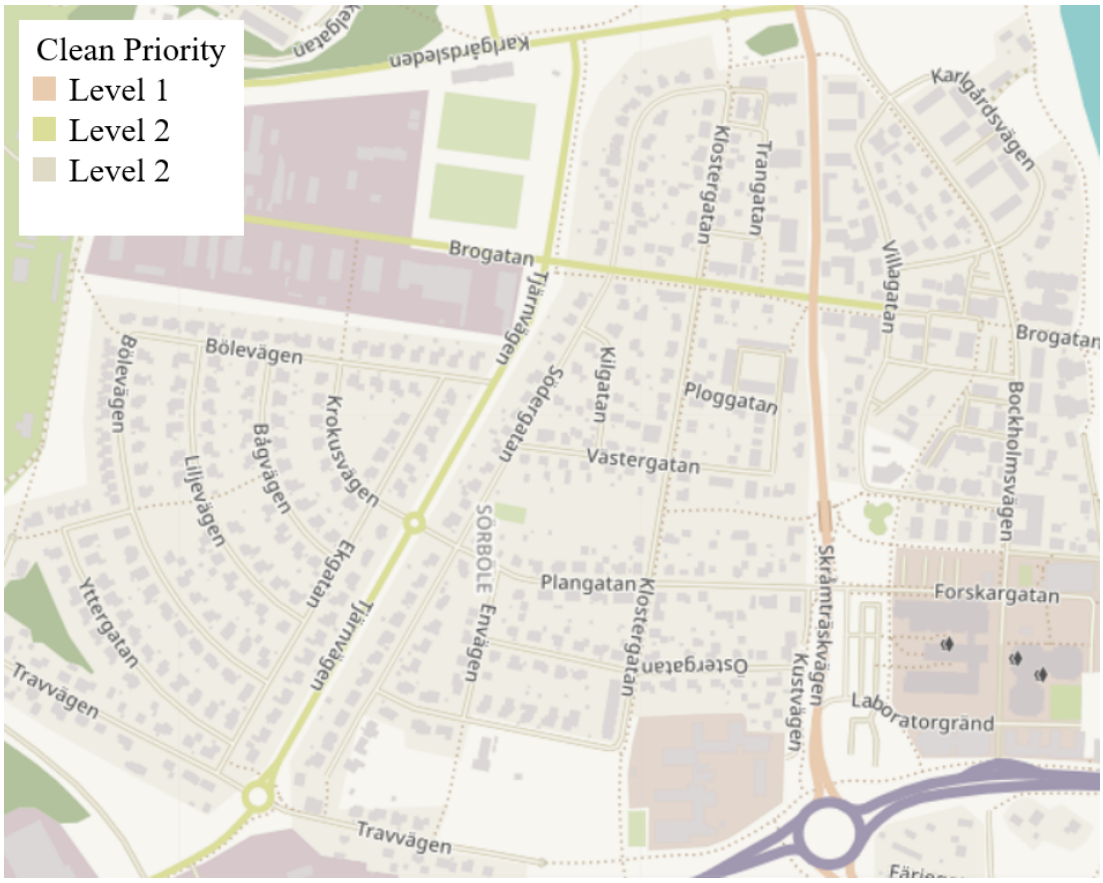


Figure 5.7: Segment setup of the example area.

There are three different waste collection processes to be taken in consideration, the one for smaller wheelie bins, which are usually assigned to private households, and the larger bins, which are placed in apartment blocks or commercial areas. For the shared bins, two cases will be considered, when one bin is shared for 5 households (Shared 1), and one bin is shared for 10 household (Shared 2). These collections are conducted by different collection vehicle types, hence it can never happen that a collection route will include both types of bins. The bin for organic waste has only one available size, 140 liters, whereas the bins for general waste can also have a capacity of 190, 370 and 660 liters. The waste management company, contracted by the municipality is only responsible for the collection and disposal of organic and general waste; recyclables are handled by a third party. For this reason, our experiments will be limited only to these waste types, for residential areas.

The experimental setup presented in this section considers only one area topology that belongs to Skellefteå Municipality as shown in figure 5.7. The legend depicts the street

color for the different cleaning priorities in case of snow. In the current case, every street is considered as a segment, where each of them has the lowest inclination degree. Segments' lengths were determined by utilizing the option "Measure distance" on Google Maps[13].

Even though ProAdaWM reasoning model supports all types of areas, for instance even those that have businesses or public facilities in them, for ease of evaluation, we consider an area only with households in it. Each registered address in a street (segment) is considered as a household; the number of addresses per each street was retrieved from Hitta.se [14] for the selected area. In the **first** use-case, private bins are considered, specifically each household owns two bins with a capacity of 140l, one for organic waste and the other for general waste. The **second** use-case considers shared bins. Specifically, for 5 (Shared 1) and 10 (Shared 2) households there is one common general waste bin with a capacity of 660l and one bin for organic waste with 140l of capacity. An average waste generation rate is considered for the experiments based on [7] for the region of Europe and Central Asia ($1.18kg/kapita/day$). It is assumed that on average 3 inhabitants live in each household.

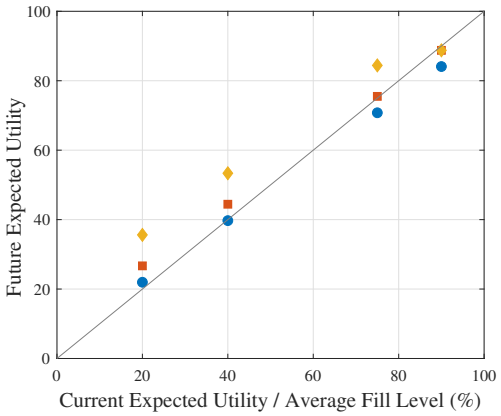
It is assumed that the waste collection vehicle is dedicated to one area only; it starts its journey from the collection point, and returns to the same point. For the present case, the collection point is situated in Degermyran, 6.3 km away from the Sörböle area[15]. The above distance is retrieved from Google Maps.

5.2.2 Results and Discussion

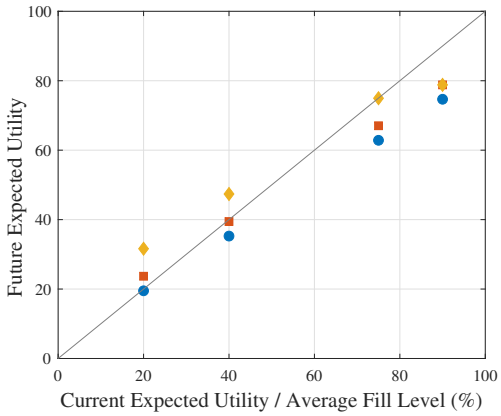
Figure 5.8 shows how the expected utility evolves based on the average fill level of the bins in one area for the three different weather cases, for the three different types of collection (depicted with different colors at the same chart), as explained in the previous section.

Based on equation 3.8, the current utility will be equal to the percentage of the average fill level of the bins in one area. For charts depicted in figure 5.8 the linear line satisfies the condition $CurrentUtility = ExpectedUtility$, hence the points below this line represent

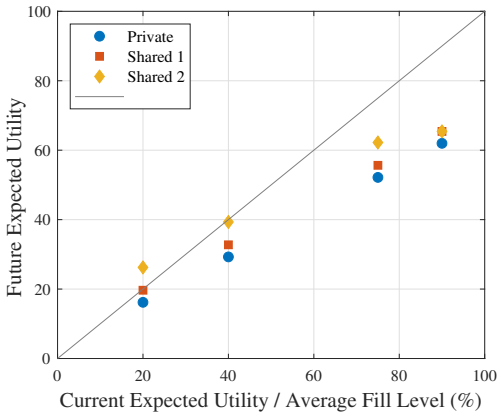
[13]https://www.google.com/maps/
[14]https://www.hitta.se/
[15]Degermyran Recycling, as reported by Skellefteå municipality.



(a) WeC 1.



(b) WeC 2.



(c) WeC 3.

Figure 5.8: Expected Utility computation for different weather cases and different collection methods.

cases where ProAdaWM reasoning algorithm recommends to reschedule the collection day before the unwanted weather event.

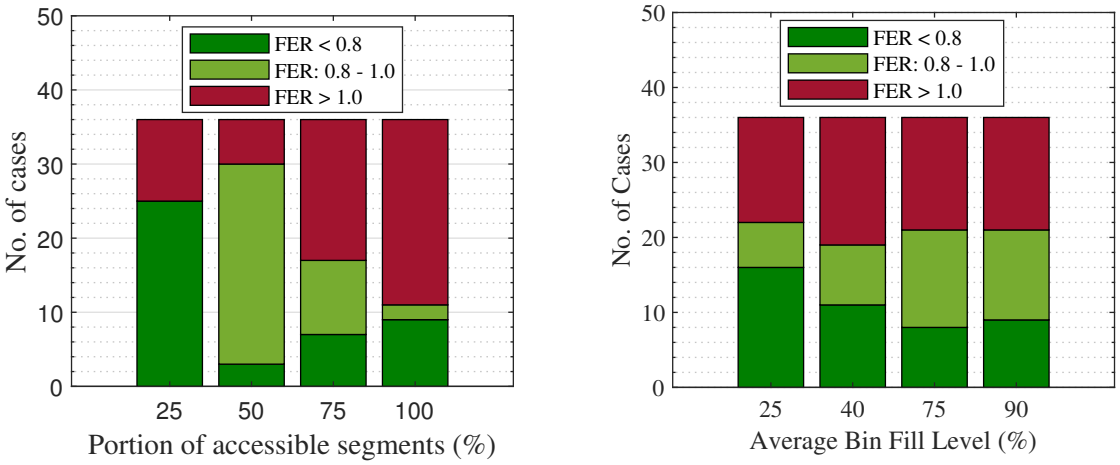
As it can be observed, the more severe the weather event, the more the chances that the collection will take place in advance; this is an expected result of the reasoning algorithm. For lower average fill levels, in most of the cases, especially for the shared bins, the collection is not rescheduled, this is also an expected behavior, since it is not beneficial or efficient to prioritize bins with less waste in them. For weather cases with more than 5mm of snowfall in the last 12 hours the reasoning algorithm suggests to reschedule all the areas with an average fill level of more than 75% to avoid overflown bins.

However, the chart in figure 5.8c shows that advanced collection should take place for an extreme snowfall (more than 20mm of precipitation) for most of the collection types even will low average fill levels. This might be disputable and non-efficient for some municipalities. Nevertheless, the areas recommended for a new collection date can be prioritized based on their utilities, hence bins of an area with expected utility of 20 will never be emptied before the bins of an area with higher expected utility.

Table 5.3: Computed Fuel Efficiency Ratio from worst to best case.

Anticipated Collection	Average Fill Level	Weather Case	Accessibility	Collection Type	FER
No	75%	WeC 1	25%	Shared 1	3.387
Yes	75%	WeC 2	100%	Shared 1	1.134
Yes	75%	WeC 3	50%	Private	0.818
Yes	90%	WeC 3	25%	Private	0.273

Table 5.3 presents the some cases of computed *FER* from the worst to the best value. For the conducted experiments, the best *FER* was obtained for the third weather case with an average fill level of 90%. The worst *FER* case is observed for the case when the algorithm does not anticipate the collection day and only 25% of the segments are accessible in the area with average fill level of 75%.



(a) Depending on accessibility level.

(b) Depending on fill level.

Figure 5.9: FER computation.

Table 5.4 shows the Fuel Efficiency Ratio for the cases explained in section 5.2.1. The green cell color highlights the cases when the collection with ProAdaWM is more effi-

cient than without it. As it can be observed in figure 5.9a, the fuel efficiency ratio highly depends on the amount of the accessible segments; meaning that, if the weather event's impact was not as severe as predicted and most of the segments (streets) will be accessible, rescheduling the areas in advance as suggested by the reasoning algorithm leads to inefficient fuel consumption. This is presented by the higher number of inefficient collections for the bars corresponding to 75% and 100% of accessible segments. However, if the city is easily impacted by snowfall, the proposed reasoning algorithm recommends more efficient collections. The chart in figure 5.9b shows similar levels of efficient and inefficient collections based on the average fill level of the bins in one area, meaning that the relative efficiency of the collection (measured by *FER*) does not depend on the fill level of the area.

5.3 Sustainability Analysis

There are several solutions [50, 19, 55] that report reduction of fuel consumption due to the adoption of smart containers and information systems for WM operations in cities. Figure 5.10 presents the effects and outcomes of deploying ProAdaWM system, mapped into the 5 sustainability dimensions of [5].

When faced with severe ice and snow in streets, WM companies prioritize their collection crew's safety, thus they might skip routes that are not safe until the conditions improve. ProAdaWM reasoning model, prioritizes the most critical streets for an anticipated collection, thus lowering the risk that the collection crews go in risky areas at unsuitable times. Safer working conditions constitute an important aspect of the *individual*'s dimension of sustainability. The above results support our initial assumptions that the proposed system allows for more fuel efficient collections when faced with problematic meteorological conditions in cities with insufficient preparedness towards these events, where collections are normally interrupted, having a direct effect on the *environmental* and *economic* dimension. More efficient fuel consumption leads to optimized resource utilization (lower costs) and to lowered carbon footprint. Another aspect of the economic dimension might be the impact of the initial investment for certain city scenarios for which a feasibility study has not been conducted. As shown in [19, 55], cost efficiency of smart waste solutions is highly dependent on waste generation patterns and waste container network, this implies that there might be cases where a non dynamic collection approach is more

suitable and good enough. In that case, costs to set up the WM infrastructure, system and maintain it might be added costs for the municipality. Hence, a cost-benefit analysis is essential to confirm that, in fact such system is necessary and beneficial.

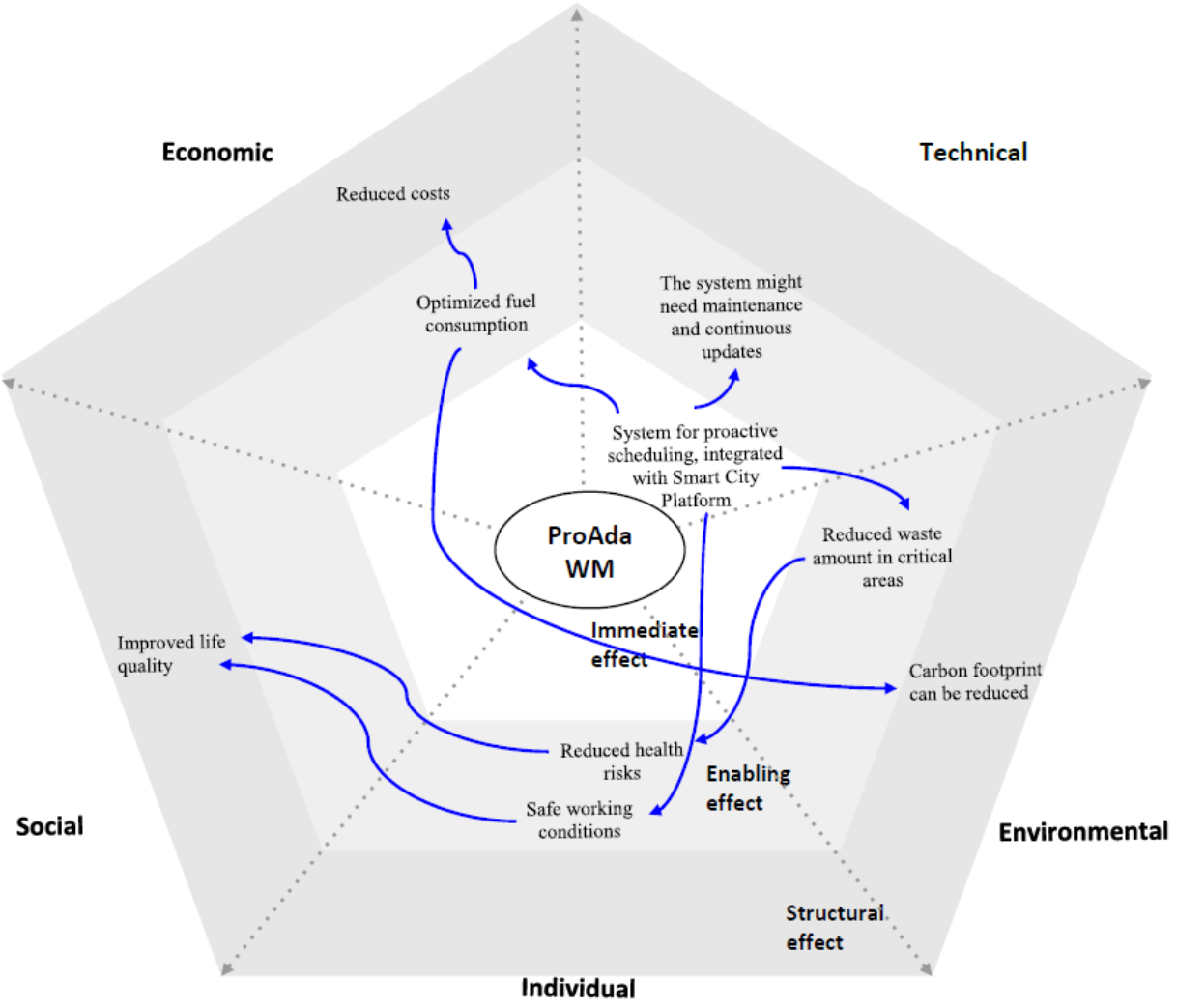


Figure 5.10: Sustainability analysis based on the five identified dimensions and systemic effects [5].

Secondly, consider for example houses outside of the city, not in very packed areas, where streets are more difficult to clear of snow; theoretically, by utilizing our system's approach there is a chance that those areas will be visited in advance if needed, giving its inhabitants the same service quality as if they lived in more central areas, thus affecting the *social* dimension by treating people equally independently of their house location.

Table 5.4: Fuel efficiency for the different cases.

Average Fill Level	Current Utility	Private Bins					Shared Bins 1/5					Shared Bins 1/10				
		Expected Utility	Percentage of accessible segments				Expected Utility	Percentage of accessible segments				Expected Utility	Percentage of accessible segments			
			25%	50%	75%	100%		25%	50%	75%	100%		25%	50%	75%	100%
s0_5																
0.2	20	21.958	3.106	1.051	0.878	0.808	26.68	2.557	0.865	0.723	0.665	35.599	1.916	0.648	0.542	0.499
0.4	40	39.709	0.291	0.861	1.029	1.119	44.431	3.070	1.039	0.868	0.799	53.351	2.557	0.865	0.723	0.665
0.75	75	70.774	0.277	0.818	0.979	1.063	75.496	3.388	1.146	0.958	0.882	84.415	3.030	1.025	0.857	0.789
0.9	90	84.087	0.274	0.810	0.969	1.053	88.755	0.289	0.855	1.023	1.112	88.755	0.318	0.941	1.126	1.223
s5_20																
0.2	20	19.498	0.322	0.952	1.139	1.237	23.691	2.557	0.865	0.723	0.665	31.612	1.916	0.648	0.542	0.499
0.4	40	35.26	0.291	0.861	1.029	1.119	39.453	0.326	0.963	1.152	1.251	47.374	2.557	0.865	0.723	0.665
0.75	75	62.844	0.277	0.818	0.979	1.063	67.037	0.295	0.873	1.044	1.134	74.958	0.330	0.976	1.167	1.268
0.9	90	74.666	0.274	0.810	0.969	1.053	78.811	0.289	0.855	1.023	1.112	78.811	0.318	0.941	1.126	1.223
s20_inf																
0.2	20	16.183	0.322	0.952	1.139	1.237	19.664	0.391	1.156	1.383	1.503	26.237	1.916	0.648	0.542	0.499
0.4	40	29.267	0.291	0.861	1.029	1.119	32.746	0.326	0.963	1.152	1.251	39.32	0.391	1.156	1.383	1.503
0.75	75	52.161	0.277	0.818	0.979	1.063	55.641	0.295	0.873	1.044	1.134	62.215	0.330	0.976	1.167	1.268
0.9	90	61.973	0.274	0.810	0.969	1.053	65.414	0.289	0.855	1.023	1.112	65.414	0.318	0.941	1.126	1.223

5.4 Summary

This chapter presented implementation and validation aspects for ProAdaWM . For validating the proposed approach, a system prototype was implemented. Section 5.1 explained details regarding the utilized technology stack and tools, how the BN was implemented and the considered assumptions for its construction, and finally the exposed API endpoints. Section 5.2 presented the metrics for evaluation, the case study modeling and assumptions, as well as the obtained results. The next chapter finalizes this thesis work by presenting the conclusions and future work.

6 Conclusions and Future Work

This chapter gives the conclusions of this thesis, revisits its contributions and presents possible future work that can applied to the same research domain.

6.1 Conclusions

The main aim of this research work was to propose a reasoning model for achieving proactive adaptation of behavior in the smart waste management context.

To achieve this, a literature review was conducted to compare existing work regarding proactive adaptation, reasoning methods and to identify challenges in existing IoT-enabled waste management solutions. In addition to that, the SDG-s more relevant to this work were presented and considered as an integral part of our proposed solution.

The ProAdaWM model was designed, implemented and evaluated for handling winter weather events for the waste collection processes. It conducts its reasoning based on decision theory, by utilizing a Bayesian Network to estimate the probability of a future event to occur, and utility theory to take the most beneficial decision. The model allows for proactive and efficient waste handling if a city's street network is susceptible towards winter weather events. However, these results are based on scenarios with assumed data and scenario setup aimed to mimic the reality. Validation with real-world data can be part of future work.

In addition, a system behavior and architecture was proposed for the ProAdaWM model. The latter can be an integrated part of any smart city platform since the communication with external components takes place with standard communication protocols. Weather information is retrieved from open data API-s and transformed accordingly to be fed to the reasoning model. A set of configuration API-s were also developed for the proposed system.

For the problem definition, design and validation phases of this work, continuous feedback from Skellefteå Municipality was taken in consideration.

6.2 Future Work

This thesis presented an initial and novel model for integrating proactive adaptation of behavior in the waste management scenario. However, this model can be enhanced by future work.

Its core reasoning component, the Bayesian Network, can be further improved by introducing more variables to it, like temperature, month of the year or by grouping the segments by more characteristics. In addition to that, once deployed, the network parameters can be learned by new incoming data-sets with methods such as *Maximum Likelihood*, the *EM algorithm* etc. [61].

The waste generation rate is an important parameter to determine the expected utility of visiting an area, at this stage the system assumes that such values are given by the experts based on average historical data. Even though we consider the seasonality of such variable throughout the year, the model can further be improved by predicting the expected waste amount in specific bins. Currently, commercial solutions such as [20] report of adding predictive analytics to their software component.

Another potential future task for the proposed architecture and reasoning model would be its validation / adaptation for different weather events. For example heatwaves can pose serious concerns when it comes to organic waste during summer months, hence action can be taken in advance for areas or segments that are expected to be the most problematic. On the other hand, some cities might suffer from floods that are caused by heavy rainfall. A similar solution, but with an adapted Bayesian Network could be utilized in this case as well.

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APPENDICES

APPENDIX A. Database Schema

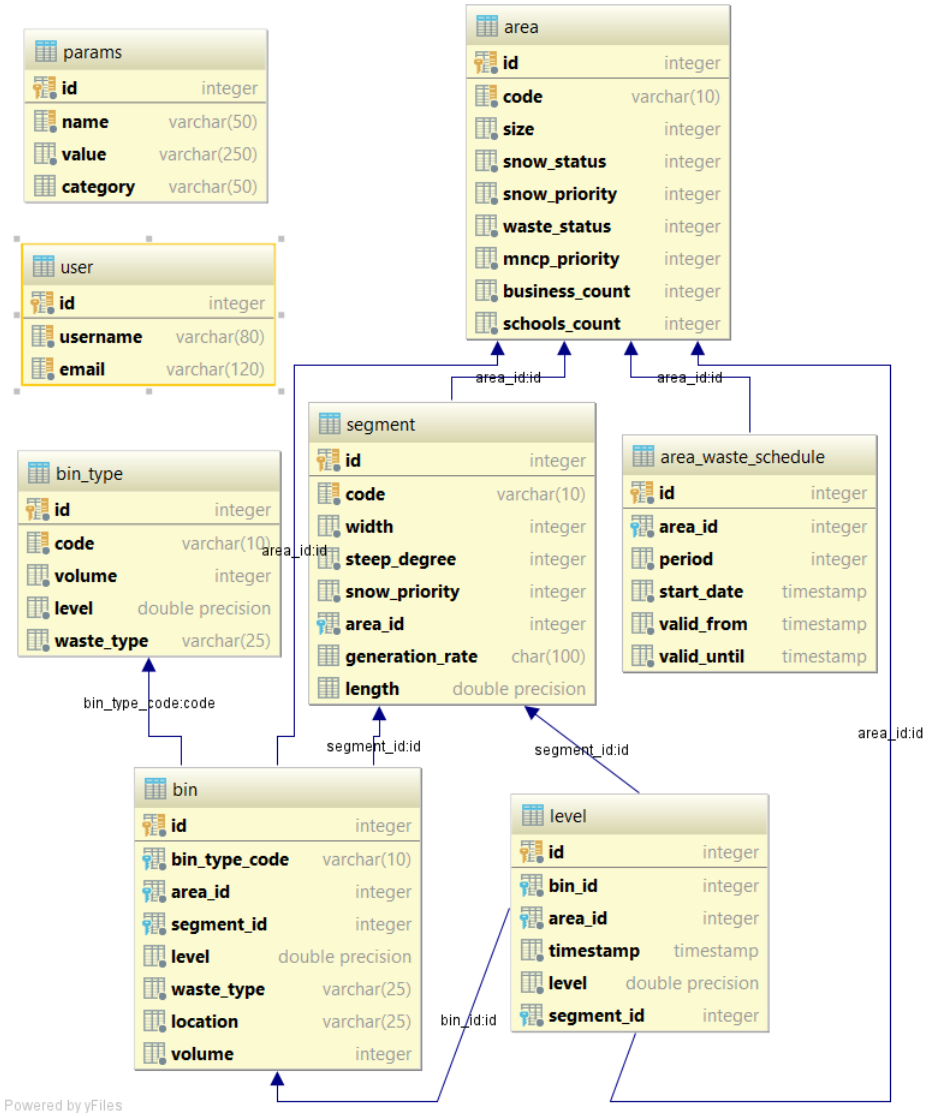

Figure A.1: Database schema.