Application of Multi-Agent Scheduling Optimisation Algorithm in Finnish Residential Energy Management System

Lappeenranta-Lahti University of Technology LUT

Bachelor's Programme in Electrical Engineering, Bachelor's Thesis

2022

Umair Muhammad Raihan

Supervisor: Dr. Arun Narayanan, Assoc. Prof. Pedro H.J. Nardelli

ABSTRACT

Lappeenranta-Lahti University of Technology LUT

LUT School of Energy Systems

Electrical Engineering

Umair Muhammad Raihan

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Bachelor's Thesis
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29 pages, 4 figures and 3 tables
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Keywords: residential load management, combinatorial optimisation, decentralisation, energy management, collective learning

This thesis explores the possibility of using a scheduling optimisation algorithm, the Iterative Economic Planning and Optimised Selections (I-EPOS), to solve load balancing problems in the Finnish residential sector. The algorithm uses principles of self-adaptive collective learning to solve the decentralised combinatorial optimisation problems, which offers flexibility and adaptability to the energy management system structure in addressing future electricity needs, as well as ensuring security for all participants in the system.

The thesis contains the necessary base knowledge of the combinatorial optimisation problem and the working principles of the algorithm itself, as well as a short performance simulation of the algorithm and recommendations on deploying it in a hypothetical Finnish household.

Acknowledgements

First and foremost, I would like to praise and thank the Almighty God, who has granted me countless blessings and opportunities to finish my thesis and my Bachelor's degree.

This thesis in particular has been an eye-opening journey into a fascinating intersection of the Internet of Things and energy technology. I would like to express my deepest gratitude to my supervisors, Associate Professor Juliano Nardelli and Doctor Arun Narayanan, for proposing this very interesting topic and guiding me throughout the entire writing process. Special thanks goes to the Head of the Degree Programme, Associate Professor Michael Child, for keeping me on track and accountable throughout my entire thesis journey.

I would also like to thank my family for believing in me when nobody would during the toughest time. Big thanks to my friends and classmates for the moral support and endless encouragement, not only during the writing of this thesis but also during my entire study in Lappeenranta. Last but not least, I would like to acknowledge anyone who reads this thesis besides my supervisors and thesis seminar instructors (and probably my family). For those of you who are in the middle of your bachelor's thesis journey, I know it sounds cliché, but I believe you can do this!

Oulu, 19 June 2022

Umair Muhammad Raihan

Symbols and Abbreviations

Abbreviations

CSV	Comma-Separated Value
DSO	Distribution System Operator
HEMS	Home Energy Management System
IoT	Internet of Things
PV	Photovoltaic
TSO	Transmission System Operator

Greek Alphabet

λ	Local Parameter, used to adjust the balance between local cost optimisation and global cost optimisation

Latin Alphabet

$\mathbf{o*}$	Optimal combination of plans
A	All agents in the system
a	Individual agent
D_C	Consumer Discomfort Rank
D_E	Environment Discomfort Rank
f_G	Global Cost Optimisation
f_L	Local Cost Optimisation
N	Node in the system
n	Number of node
N_A	Aggregator Node

N_C	Child node
N_L	Leaf node
N_R	Root node
o	Combination of plans
P	A set of plans
p	A single plan
P_S	A selected plan
R_A	Aggregated Response
R_G	Global Response
S_P	Overall Preference Score of a Plan
U	Unfairness

Contents

1 Introduction

1.1 Background

In today's modern world, a significant part of our lives has become increasingly dependent on electronic devices. Our houses nowadays are filled with electrical home appliances that need a constant supply of electricity, not to mention other energy-intensive consumer devices that we frequently use every day. These consumer devices and appliances have become an inseparable part of our daily lives, and the amount of their utilisation in the ever-growing world keeps increasing every single day. As a result, the stability of the power grid that supplies our daily electricity needs becomes one of the most important aspects of the functioning of modern human society, which is why ensuring a sustainable operation of the power grid becomes highly important in sustaining modern human lives. The challenges that come with it lie on, among other things, implementing new ideas and technologies to solve load balancing problems.

Electronic devices and appliances are not all created the same. Each of them has its own operational preferences and behaviour, different type of consumers might want to use it in different ways, and this naturally creates a difference in the load demand of different consumers. This demand has to be actively monitored and controlled every day, which traditionally has been the job of the Transmission System Operator (TSO) as well as the Distribution System Operator (DSO) on both the national load level (high voltage level) and the residential load level (low voltage level), respectively. However, the shift from this energy management systems method seems to be happening recently with research and efforts have been spent to investigate how to reform the current energy management system to address future energy needs. This movement happens mainly in response to the increase (and more potential future increase) of renewable energy production due to countries aiming to accomplish their 2050 climate targets (European Council, 2019) and the increase in popularity and implementation of the smart grid.

1.2 Research Problem

In recent years, electricity service providers have been exploring the possibility of a consumer-side load balancing system. The increase in renewable energy production is stated as one of the key reasons that have launched this idea to the surface due to the fact that a majority of renewable energy production is taking place close to the point of consumption. (Barancourt, 2019) At the same time, the rise in popularity of the smart grid emphasises the importance of designing a load-demand balancing system that is more favourable to the consumer. (Mammoli et al., 2019) Coupled with the advancement in edge computing and the Internet of Things (IoT), it should be even more possible now than ever to design and construct an energy management system that is more consumer-friendly and efficient, especially in the residential sector.

The residential sector, in particular, is an interesting study case for this kind of technology. The sector has a big impact on the overall power grid consumption level, which globally represents around 30% to 40% of total energy usage in 2011 (Alberini & Filippini, 2011) and keeps ever increasing. This number outlines a massive potential for a collective demand-side load balancing not only in a single household within individual appliances but also within a residential community with an aim to better sustain the power grid in general. These are big incentives that, to the author's knowledge, have not been fully explored from a practical standpoint.

There has been increasing attention to this issue from the academic community and industry players alike, with research has been conducted to try to find ways of implementing an efficient and accurate demand-side energy management system. Earlier works including solutions from Pournaras et al. (2018), Al-Hinai and Haes Alhelou (2021), and Bremer and Lehnhoff (2019), as well as an in-depth investigation by Fanitabasi and Pournaras (2020), are only some of the researches that have happened in this relatively young research field. In addition, Barancourt (2019) from the French multinational IT service and consulting firm Atos has argued the need to deploy such technology as "vital" for the future energy system.

1.3 Current State and Future Direction of Energy Management Systems

Load balancing is one of the most important parts of power grid operation. Traditionally, this process of constant monitoring and balancing of power grid load and supply is performed by the TSOs at the national level and the DSOs at the residential level. (Barancourt, 2019) However, as more new electronic devices and appliances are being produced every single day, as well as the constant growth of the world population that increases the demand and utilisation rate of these devices and appliances, the rigidity of this traditional system often fails to stand the test. One of the most challenging problems these two trends bring for electricity providers is the sudden increase in demand during peak hours, sometimes even more than normal. (Muralitharan et al., 2016) This problem, among other things, contributes to even more frequent blackouts in high-density population centres. Urgent action is needed to re-evaluate and reform the current traditional power grid design in order to adapt to the future needs of society.

In recent years, a new paradigm of load balancing systems has emerged due to the limitation of the traditional energy management system design mentioned above. Electricity providers are considering shifting (or at least distributing) load balancing responsibility from TSOs and DSOs down to the consumer level. The development of the smart metering system that can provide detailed information on electricity consumption with an accuracy of up to a minute has enabled the increase in visibility of individual electricity consumption to customers, which made tracking personal electricity usage easier than ever. The advancement of edge computing and data science, as well as smart metering mentioned above, can provide an impetus toward developing a more advanced and flexible demand-side load balancing system.

Currently, at least two approaches are being actively explored in consumer-level load balancing systems. The first approach is an active, response-based load balancing system. The program that implements this approach can adjust a consumer's electricity consumption by constantly decreasing or increasing electricity loads or allocation in response to shortage or excess electricity supply and demand from the electricity provider in a real-time precision. A few examples that used this approach can be investigated further from the works of Shakeri et al. (2017) and Nilsson et al. (2018).

The second approach is based on the optimisation of event scheduling. This approach assumes that each consumer within an electricity network must have one and only one electricity usage plan that is preferred the most out of several possible plans that the consumer could use. This approach aims to find the most optimum plan for each consumer that satisfies the initial goal set by the system designer, whether it be achieving the most effective electricity consumption of the system, satisfying all participants in the system or everything in between. Thus, in theory, depending on agreements between consumers and the service provider, we can use this approach to" force" good habits of using energy more efficiently on the consumers without them ever feeling forced to do it. One of the algorithms that become the centre of this paper, the Iterative Economic Planning and Optimised Selection (I-EPOS), aims to solve the load balancing problem using this approach.

1.4 Research Goals

This thesis aims to figure out how the future demand-side energy management system can be managed and structured using the I-EPOS algorithm as the main decision-making algorithm on a household level. The principles of decentralisation and collective learning that the I-EPOS algorithm brings are powerful tools to promote sustainability, fairness and security in a critical public sector such as the residential energy management system, also known as Home Energy Management System (HEMS). The study conducted in this thesis could open up new knowledge to the reader on the implementation of one particular algorithm, the I-EPOS algorithm, in tackling the load demand balancing problem in a residential area.

To achieve this goal, the author conducted a literature review to give necessary base knowledge before conducting the simulation, as well as supporting the author's arguments in the Discussion section. It is structured around the following questions:

1. What is the current state of the energy management system, and what are the

different methods currently available for demand-side energy management?

2. How does the I-EPOS algorithm decide the most optimum solution to a combinatorial optimisation problem given a set of pre-defined selection options, constraints and agent preferences?

3. How can the I-EPOS algorithm be implemented in a hypothetical Finnish house and, even more importantly, in a local Finnish residential grid?

1.5 Scope and Limitations

The research in this thesis focuses particularly on the structure of HEMS using a specific multi-agent system planning optimisation algorithm (i.e. the I-EPOS algorithm) in a Finnish household. The research does not take into account any self-energy production that is produced by the consumer (e.g. energy produced by solar PV panel array installed on the house roof) nor energy storage of any form. The thesis strictly looks at how the I-EPOS algorithm works and how it can be utilised to handle load balancing tasks of several major appliances in a Finnish household.

1.6 Structure of Thesis

The thesis is presented following the IMRaD (Introduction, Methods, Results and Discussion) structure with a few modifications. The Introduction section briefly explained the research background, research problem, a brief explanation of the current state and future direction of the energy management system, research goals as well as the scope and limitations of the research. It is followed by a literature review of the Combinatorial Optimisation Problem and the I-EPOS Algorithm. The Methodology section explains how the simulation was carried out. The Results section contains the results of the load scheduling simulation of five major home appliances in a hypothetical Finnish house using the I-EPOS algorithm. A short analysis of the simulation result is presented, followed by discussions on how the residential energy management system would be structured around the structure principle of the I-EPOS algorithm. Finally, the conclusion section concludes the thesis as well as gives a few suggestions for future research in this field.

2 Literature Review

2.1 Combinatorial Optimisation Problem

In the field of mathematical optimisation, time-dependent scheduling optimisation problems can be classified as combinatorial optimisation problems. The combinatorial optimisation problem is a mathematical problem that aims to find the most optimal solution from a finite set of objects. (Schrijver, 2003) The solution could be of an exact value, a set of values or approximation values.

The desired accuracy of solutions produced by a combinatorial optimisation algorithm highly affects the speed and resources needed: the more precise an algorithm needs to achieve, the more computational resources it needs and the slower the result will come out. This is because, among other factors, most combinatorial optimisation problems are categorised as *NP*-hard problems in terms of complexity. (Turky et al., 2020) Gawiejnowicz (2020) define *NP*-hard problems as:

> If for a problem P and any $P' \in NP$ we have $P \propto P$, the problem P is said to be *NP*-hard. (Gawiejnowicz, 2020, p. 36)

In other words, a problem P is *NP*-Hard if any solution to P is verifiable in polynomial time. Later, he remarks:

> The problems which are *NP*-complete (*NP*-hard) with respect to the binary encoding scheme become polynomial with respect to the unary encoding scheme. Therefore, such problems are also called *NP*-complete (*NP*-hard) in the ordinary sense, ordinary *NP*-complete (*NP*-hard) or binary *NP*-complete (*NP*-hard) problems. (Gawiejnowicz, 2020, p. 36)

As the complexity increases, the computational resources needed to find a solution (or a set of solutions) to an *NP*-hard problem increase on polynomial factor in relation to time. Due to this limitation, as the number of search spaces increases, most combinatorial optimisation algorithms resort to either aim to yield an approximate solution (or a set of solutions) as close to the exact answer as possible or by heuristically searching for the best solutions within a number of possible solutions. (Gawiejnowicz, 2020, p. 24-28) One famous example of the combinatorial optimisation problem is the Traveling

Salesman Problem. The essence of this problem is to find the least route a salesman needs to travel to visit all listed cities. The load balancing problem can also be categorised as a combinatorial optimisation problem, as the most optimum load balance can be found through performing a defined mathematical optimisation technique that iteratively goes over a search space in the form of load demand data.

In the field of multi-agent system planning optimisation a few solutions that utilise concepts of combinatorial optimisation are COHDA (Hinrichs et al., 2014), EPOS (Pournaras et al., 2017) and I-EPOS. (Pournaras et al., 2018)

2.2 The I-EPOS Algorithm

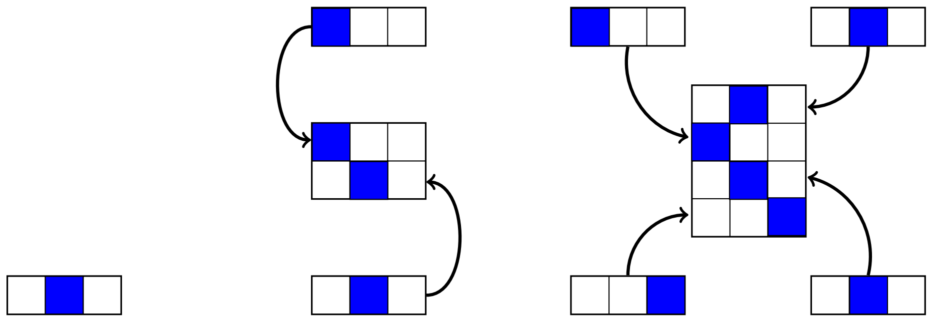
The I-EPOS algorithm is the next evolution of the EPOS algorithm. Both algorithms are quite similar in the way that they intend to solve time-scheduling optimisation problems within a large multi-agent network system. One major difference that the I-EPOS algorithm introduces to improve upon the EPOS algorithm is the iterative problem-solving process. The I-EPOS algorithm allows each agent in the system to generate their own set of plans P and then put weights (preferences) on each plan in the set ($p \in P$), in which there must be one and only one plan that has the highest preference among other plans in the set.

The highest plan in the set is defined as the selected plan P_S. The selected plan of one agent is then aggregated along with other agents' selected plans to form an aggregated response R_A. A vector that contains all selected plans within a system is then compiled to form a global response R_G. (Pournaras et al., 2018, p. 5) I-EPOS can then optimise the global cost fG by optimising for g. However, since I-EPOS allows each agent to select their own plans out of a set of agent-generated plans, I-EPOS is also able to optimise the local cost fL by optimising for the difference between each agent's plan preference and selected plans. This means that the algorithm can be used in various applications, including the load balancing problem, with a high degree of flexibility.

An optimal combination of plans $\mathbf{o}*$ can be defined as:

$$\mathbf{o}* = arg\,min\, f_G(\sum_{a,o} o), \tag{1}$$

where a is an individual agent and o is a combination of plans. (Pournaras et al., 2018, p. 5)



(a) Selected Plan (b) Aggregated Response (c) Global Response

Figure 1: Illustration of the plan aggregation process in I-EPOS (Adapted from Pournaras et al. (2018, p. 3)

In I-EPOS, the priority on global cost optimisation and local cost optimisation is controlled by a local parameter λ, with $\lambda = 0$ sets the algorithm to optimise solely on minimising global cost and $\lambda = 1$ sets the algorithm to optimise solely on minimising the local cost. Global cost can be defined as the cost that is inflicted on the whole system in order to execute a certain set of plans for every agent in the system, while local cost is the amount of discomfort an individual agent is experiencing while executing the plan selected by the system compared to their most preferred plan. The solution with the most optimum global cost is not guaranteed to have the most optimum local cost and vice versa. This is where another metric is defined to explain this difference: Unfairness.

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Unfairness U is defined as "the deviation of discomfort values across all agents", (Fanitabasi & Pournaras, 2020, p. 119885) which measures whether all agents in the system get the same benefit of getting their most preferred plan. (Pournaras et al., 2018, p. 6) Unfairness U is calculated by normalising the standard deviation σ of local costs for all plan selections with the mean μ of selected plan's local costs:

$$U = \frac{\sigma\{f_L(s_a) \mid a \in A\}}{\mu\{f_L(s_a) \mid a \in A\}}, \tag{2}$$

where s_a is the selected plans and $a \in A$ is an individual agent. (Pournaras et al., 2018, p. 6)

In their paper, the algorithm designer structured the multi-agent system in a tree topology structure. The tree topology "...serves the purpose of computing the aggregated and global response in an efficient and accurate way..." (Pournaras et al., 2018, p. 6). Unlike the graph topology, the tree topology is structured under a set of rules, for example under a node n there must be a certain amount of child node N_C. Due to the acyclical nature of the tree topology, the I-EPOS algorithm divided the decision-making process into *bottom-up* and *top-down* phases.

In the *bottom-up* phase, each leaf node N_L (i.e. the bottom-most node in the topology) create a selection of plans and select only one plan they prefer the most. create a selection of plans and selects only one plan they prefer the most. It is assumed at this point that each leaf node does not know what kind of plan the other leaf nodes created or chose or what the aggregated response looks like when their own plan is combined with other nodes' plans. The preliminary set of plans is then sent to their parent node, which acts as the aggregator node N_A between two leaf nodes. N_A computes and selects a preliminary selection of plans only for the nodes inside the branch they manage (since they do not have the knowledge of other branches), which is then passed to their parent node. This process is repeated for each node in an upward direction until it reaches the root node N_R. N_R then computes an effective selection of plans by optimising the global cost or the local cost as, by this point, the root node will have complete knowledge on all plan selections in the system.

In the *top-down* phase, agents "...approve/reject the preliminary selections..." and update the aggregated and global responses for all agents. (Pournaras et al., 2018, p. 10) In other words, the computation result of f_G by N_R, as well as R_A from all agents, are informed back to every agent. In this phase, an agent can change their plan selection "...if and only if all its ancestors approve the preliminary plan selection." (Pournaras et al., 2018, p. 10) This *bottom-up* and *top-down* cycle will keep happening iteratively, enabling every agent to optimise their plan selection with the system's goal. This is how the I-EPOS decentralised collective learning works while at the same time trying to achieve fast decision-making.

The decentralised nature of I-EPOS spreads the responsibility of decision-making to not only one agent/node but also to all agents/nodes in the system. The algorithm also only requires each agent to pass around their plan selection to other agents, allowing each node to make an accurate and informed decision without having to transmit all unnecessary data to other nodes above them. It allows each agent to keep their sensitive personal information, theoretically preventing the leak of personal and other sensitive data that criminals can exploit. It can increase the system's security, which is beneficial for all participants in the system.

3 Methodology

This thesis contains a literature review that explores the state of the energy management system, as well as gives a short explanation of the combinatorial optimisation problem and the working principle of the I-EPOS algorithm. It was conducted to provide the base knowledge needed to understand the key arguments proposed later in the Discussion section. This research also used a computer simulation to test the formation of energy usage scheduling with the I-EPOS algorithm on a synthetic dataset of a few major home appliances.

3.1 Simulation Method

The software used for the simulation is the I-EPOS Exemplar Software Suite. The software is a *Java* executable file licensed under the GNU General Public License v2 (GNU GPL v2). There is a short explanation of how to use the software in three different usage scenarios[1], as well as a more detailed guide to customising more aspects of the software.[2] At the time of writing, the software is still in the development phase, and the author could not find a Graphical User Interface (GUI) despite its appearance on the official website. The software can be downloaded right from its GitHub page[3] in a *zip* file that must be extracted. Inside, a *.jar* executable file is executed to start the simulation. It must be noted that since the software is implemented in *Java*, the Java Runtime Environment (JRE) must be installed in the local machine to run the software. After the simulation is fully performed, it will create a new folder named "output" that contains the results in files formatted as Comma-Separated Value (CSV) and images illustrating the selected plans of each agent after each simulation runs.

To get the intended result from the simulation, a dataset directory containing plans for each agent must be provided. The configuration file that comes with the software suite is customised according to the software manual guide. A plan must consist of a preference score and a vector of comma-separated values, all written in a single line

[1] https://epos-net.org/software/exemplar/
[2] https://github.com/epournaras/EPOS-Manual/blob/master/manual.pdf
[3] https://github.com/epournaras/EPOS/releases

separated by a colon (:). For the purpose of this thesis, a preference score ranging from the lowest 1 to the highest 10 was given for each plan, while a 24-column vector on each plan indicates the power used in Watt (W) by an appliance in active use and 0 when it is inactive. Each column in the vector represents one hour in 24 hours period. Due to the complexity of modelling electricity load demand in a real-world scenario, usage plans for each appliance were made manually based on both the author's experience and previous similar research.

There are five home appliances included in the simulation: television (TV), washing machine, dishwasher, coffee maker, and electric oven. In order to model the usage of each appliance, the author used several supporting resources. The author founds the works from Fanitabasi and Pournaras (2020) and Shakeri et al. (2017) to be very useful in giving a guideline on how to model the usage of various common home appliances. Another important resource that was used is the work of Richardson et al. (2010), who created a load demand model for the United Kingdom (UK) residential sector in the form of an Excel macro file that is free to use for everyone. Table 1 below contains a detailed list of appliances used in the simulation, while Table 2 illustrates the usage schedule of an appliance (TV) in the simulation.

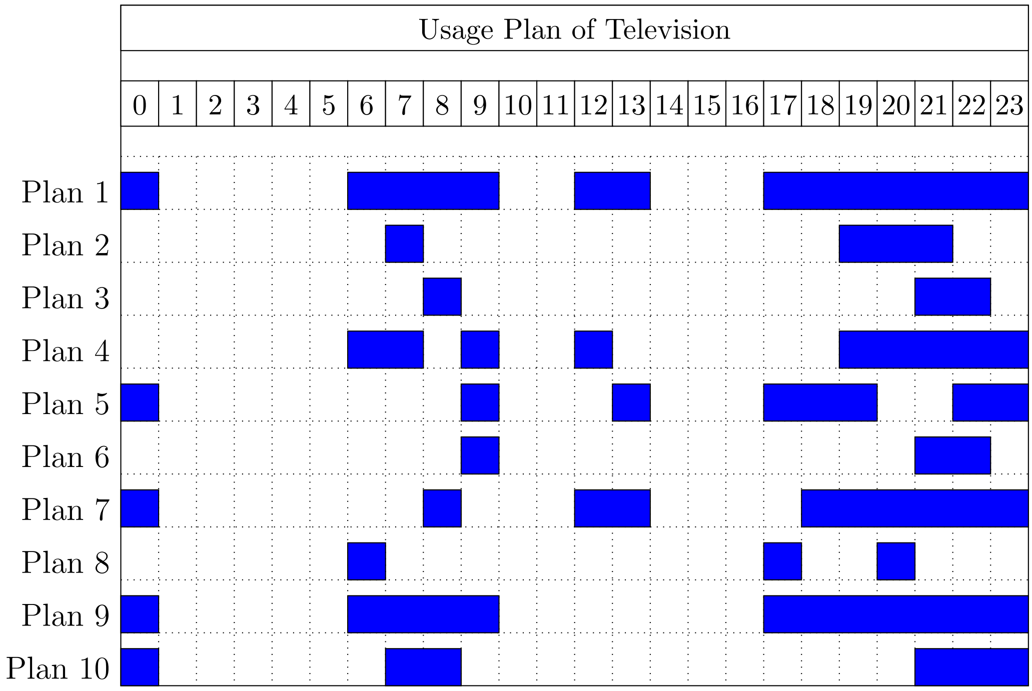
Table 1: List of home appliances included in the simulation with its essential specifications

Appliance	Model	Power Rating (W)	Prime Time[1]
TV	LG 43" UP75 LED TV	85	21:00-24:00
Washing Machine	Electrolux EW7F6669Q6	570/cycle[2]	17:00-18:00
Coffee Machine	Moccamaster HB951-AO	1,500	07:00-09:00
Dishwasher	Siemens SD6P1S	2,400	08:00-09:00
Oven	Samsung NV68N3372BM	1,700	18:00-19:00

[1] The average time period when an appliance is in high usage among the majority of Finnish households.

[2] One washing cycle includes the prewash, washing, rinsing and spinning stage.

Table 2: Illustration of the generated usage plans of television, taken from the dataset used in the simulation



3.2 Plans Preference Scoring Method

The overall score of a plan S_P consists of two components: Consumer discomfort ranks D_C, and environment discomfort ranks D_E. D_C is the discomfort value that a plan causes to the consumer (e.g. radically different plan from previous usage behaviour would cause a certain level of discomfort for the consumer), while D_E is the discomfort value that a plan causes towards the environment (e.g. using an appliance more than the normal usage or during the peak hours would inflict certain damage to the environment due to the need of increasing electricity generation). Every plan was ranked on a scale of 1 to 10 for each factor, with 1 being the most preferable (inflicts the least discomfort) and 10 being the least preferable (inflicts the most discomfort). To get S_P, 55% of the D_E and 45% of D_C numbers values were taken and then summed together.

$$S_P = (D_C * 55\%) + (D_E * 45\%) \tag{3}$$

Each appliance's current consumer usage behaviour is used as a baseline for D_C, i.e. it automatically gets the number 1 as its D_C. The ranking for consumer discomfort was decided before the ranking for environment discomfort. After that, a percentage from both ranks was taken as S_P, as explained in Equation 3. Table 3 shows an example of how the TV plan scoring process is done. By following this method, the research intends to consider both consumer and environmental aspects of the energy management system.

Table 3: Scoring Table for Television usage plans

Plan	Environment Discomfort Rank	Consumer Discomfort Rank	Overall Preference Score
1	9	1	5.40
2	8	2	5.30
3	10	3	6.85
4	7	5	6.10
5	6	4	5.10
6	3	7	4.80
7	2	6	3.80
8	4	8	5.80
9	1	10	5.05
10	5	9	6.80

4 Results

The simulation showed that the I-EPOS algorithm could quickly minimise variance in the system's global costs. In every simulation condition, the algorithm can find optimum solutions within only 10-15 iterations on average. In fact, as the value of λ increases, the algorithm finds optimum solutions even faster. Figure 2 shows the changes in global cost value as the algorithm iterates over a set of available plans.

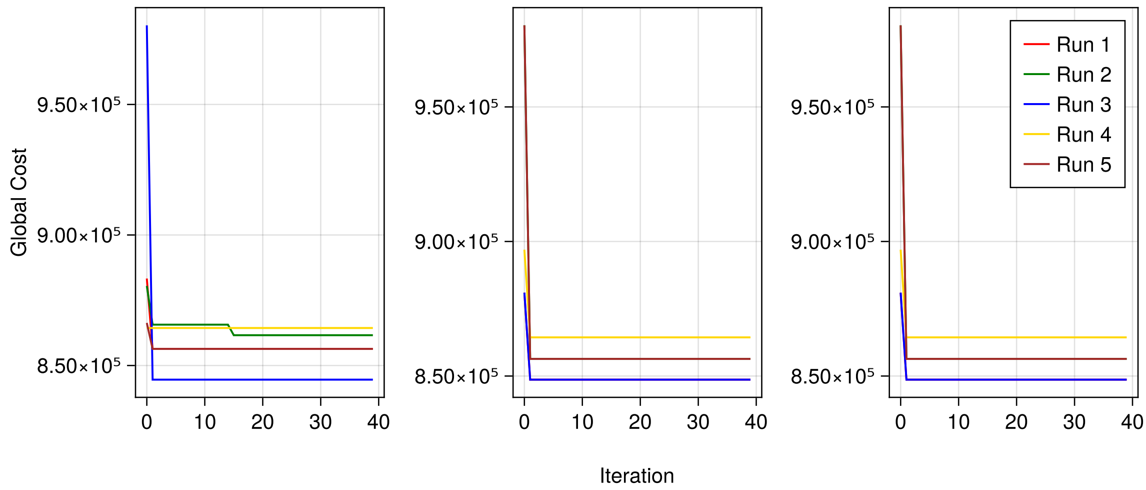


Figure 2: Global cost changes over iterations when $\lambda = 0$, $\lambda = 0.25$, and $\lambda = 0.5$ from left to right.

It was also found that as the λ value increases after 0.5, the global cost graph becomes flat over all iterations as the algorithm neglects optimisation in global cost variance. This is due to a priority shift towards optimisation of local cost variance on higher λ values.

Another metric that was investigated is the unfairness rating. As we are not optimising for unfairness in all simulation runs, the first graph in Figure 3 on the left when $\lambda = 0$ shows that the unfairness level is highly varied over iterations as well as in different simulation runs; thus, no definite conclusion can be drawn. The next two simulation conditions ($\lambda = 0.25$ and $\lambda = 0.5$, both on the middle and the right, respectively) showed a more stable progression of unfairness over iterations. However, there is still some difference between one simulation run with another.

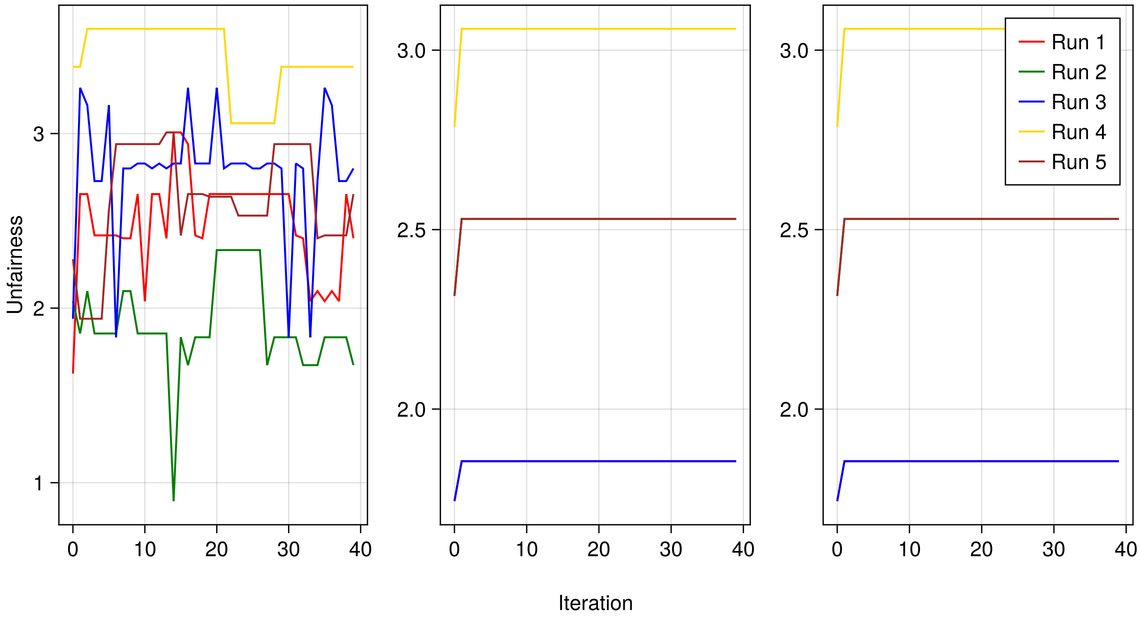


Figure 3: Changes in unfairness over iterations when $\lambda = 0$, $\lambda = 0.25$, and $\lambda = 0.5$ from left to right.

5 Discussion

From the simulation result, we can see how different priority levels in global cost optimisation affect the convergence speed of the algorithm as well as the most optimum global cost value at the end of the iteration. We can relate global cost in HEMS with the amount of energy used by the household, while the λ value can be related to the level of the system's preference towards optimising energy consumption. Besides global cost, the unfairness rating is also an important metric to watch in order to build an energy management system that is beneficial for the consumer. While global cost can be considered a measure of consumer electricity consumption, unfairness can be considered a measure of consumer dissatisfaction with the selected plans. Both metrics are equally important in the grand scheme of the energy management system, so there should be a balance between both. The findings from the simulation in the previous section can be utilised to adjust both settings in real-world use cases.

From the system architecture point of view, how the demand-side load balancing system under I-EPOS can be structured? As proposed by Pournaras et al. (2018) in their paper, the multi-agent system can be built in a tree topology, specifically the binary tree topology. The system could consist of multiple home appliances as individual agents and a smart home controller acting as both aggregator and the main root node. Each node/appliance can locally form its own usage schedule by combining past usage data and automatic plan generation using various techniques such as classification (Fröhling, 2017), Markov decision processes (Pandey et al., 2016), and other techniques. The rank/scoring of each plan could then be decided locally based on estimated consumer discomfort, electricity prices, estimated emission, etc. This data would then be passed to the decision-maker system, which is entirely run by the I-EPOS algorithm, to find an optimum set of plans for the whole appliances in the household. The smart home device, which acts as the root node, can be used to calculate an estimated amount of power needed based on the optimum plan selections solution and only ask for that amount of electricity from the DSO. This approach looks restrictive at first, but the iterative and collective learning nature of I-EPOS adds flexibility to the system to unexpected events, as the whole system is required to keep learning and adapting to changes.

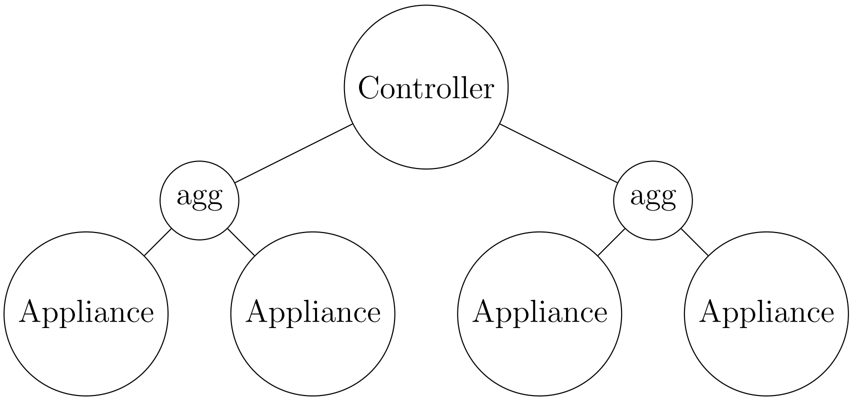


Figure 4: Proposed home energy management system model under I-EPOS. Both aggregator (agg) nodes and the root node is abstracted in the main processing unit. (in this case the smart home controller)

With the advancement of edge computing and smart home devices, consumers in the residential community do not need to worry about installing too many electronic devices or allocating big spaces in their homes just for storing all the processing units to do the required calculations. Theoretically, the whole abstraction can be done inside a smart home controller device, i.e. usage data gathering, plan generation, and optimisation processes can be done all inside one or two of these devices.[4] Thus in a perfect world, smart home device manufacturers only need to push a major firmware update to incorporate I-EPOS to their existing devices without doing a major physical reinstallation of their customer's smart home system. This would benefit both consumers and smart home monitoring device manufacturers.

[4]The configuration could be in the form of a smart home controller combined with an external home monitoring device or a single board computer (SBC) such as Raspberry Pi

6 Conclusion

In the author's opinion, the potential for developing a demand-side energy management system in the residential sector is something that the industry cannot close their eyes off. We are now at the moment of transition from a traditional grid system to a future system in smart grid. In a decentralised electricity market like Finland and the Nordics, there is a big opportunity for anyone who wants to take a chance designing such an energy management system in the residential sector. The proposed framework offered in this thesis shows that it is, in theory, possible to design such a thing.

Future research can expand this thesis by including real data, for example, on Finnish household load profile, electricity price, and real-world consumer behaviours, into the simulation. Furthermore, future research can implement a concrete energy management system prototype based on the proposed framework in this thesis and test the viability of building such project on a scale. The simulation results presented in this thesis must also be further validated to determine whether the selected plan list is indeed the most optimum and correct answer given the defined constraints.

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