Department of Mathematics and Systems Analysis

Optimization approaches for dynamic environmental and energy management problems

Juha Mäntysaari

Aalto University

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Optimization approaches for dynamic environmental and energy management problems

Juha Mäntysaari

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Abstract

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Abstract

Today, in problems related to environmental decision making as well as to the use of electricity, one has to take into account time dependent effects, such as prices or system dynamics, together with multiple objectives. These problems are examples in which one can utilize dynamic multiobjective and bi-level optimization. These problems can have multiple conflicting objectives, such as the minimization of costs and the maximization of comfort. In environmental decision making, the objectives may relate to harmful impacts and the interests of the stakeholders. The problems may contain complex time dependent dynamics describing the reactions to changes in the operating environment and the choices made. Moreover, the situation may be of the leader-follower type where the leader tries to maximize the overall benefits by taking into account the reactions of the followers. This dissertation addresses these kinds of real-world problems in energy management and environmental decision making. The problems considered include the multiobjective optimization of an electrically space heated home and the regulation of a lake-river system. The dissertation also studies a new model in electricity markets where a group of consumers are working in cooperation. Additionally, the problem of combining the production planning and energy management in the process industry is examined.

Typically, there are no generally applicable standard solution methods for dynamic multiobjective or bi-level optimization problems. This dissertation develops new solution methods for the practical case studies mentioned above. These methods include price coordination, dynamic interval goal programming and a combined goal programming and constraint method. The applicability of the methods is tested and verified numerically with real life data. The dissertation also develops practical implementations of the methods in a spreadsheet environment. The implementations proved to be successful. The space heating model gives the user a possibility to optimize heating costs by taking into account the hourly varying goal for the indoor temperature. The model showed that cooperation of the consumers in energy purchasing is also possible. The Finnish Environment Institute utilized the lake-river regulation model in the real development and evaluation of the regulation policies. In the industrial energy management problem, the price coordination method produced solutions for the problem quickly, although, in general, the convergence of the coordination method cannot be guaranteed.

Keywords dynamic multiobjective optimization, bi-level optimization, price coordination, demand side management, space heating, electricity markets, lake-river regulation, energy management in process industry

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Juha Mäntysaari

Väitöskirjan nimi
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Tiivistelmä

Tänä päivänä niin ympäristöpäätöksenteossa kuin sähkön käytössä on otettava huomioon ajan mukana kehittyviä ilmiöitä, kuten hinnat ja ilmiöiden dynamiikka, ja monia eri kriteereitä. Tämän tyyppiset tehtävät ovat esimerkkejä, joissa voidaan hyödyntää dynaamista monitavoiteoptimointia ja kaksitasoista optimointia. Tehtävissä saattaa olla useita toisilleen mahdollisesti vastakkaisia tavoitteita, kuten kustannusten minimointi ja mukavuuden maksimointi. Ympäristöalalla kriteerit voivat liittyä tarkasteltavissa hankkeissa syntyviin haittoihin ja sidosryhmäintresseihin. Tehtävät voivat myös sisältää kohdesysteemeihin liittyvää ajasta riippuvaa dynamiikkaa. Lisäksi tilanne voi olla myös johtaja-seuraaja tyyppinen asetelma, jossa johtaja pyrkii maksimoimaan kokonaishyötyä ottaen huomioon seuraajien reaktiot. Tässä väitöskirjassa tarkastellaan tämänkaltaisia reaalimaailman energianhallinnan ja ympäristöpäätöksenteon ongelmia. Tarkasteltavia tehtäviä ovat monitavoitteinen sähkölämmitteisen omakotitalon lämmitysongelma ja vesistön säännöstelyn ongelma. Väitöskirjassa tutkitaan myös uutta toimintamuotoa sähkömarkkinoilla, missä kuluttajat toimivat yhteistyössä. Lisäksi tarkastellaan tuotannon suunnittelun ja energianhallinnan yhdistämisen ongelmaa prosessiteollisuudessa.

Dynaamisiin monitavoite- tai kaksitasoisiin optimointitehtäviin ei ole olemassa valmista yleisesti sopivaa ratkaisumenetelmää. Tässä väitöskirjassa kehitetään edellä mainittuihin reaalimaailman ongelmiin soveltuvia uusia ratkaisumenetelmiä. Näitä ovat hintakoordinointi, intervallitavoitemenetelmä sekä tavoite- ja rajoiteyhtälöiden yhdistetty menetelmä. Menetelmien soveltuvuutta testataan ja niiden toimivuus todennetaan reaalimaailman ongelmien numeerisilla esimerkeillä. Väitöskirjassa tarkastellaan myös kehitettyjen menetelmien käytännön toteuttamista taulukkolaskentaohjelmalla. Nämä toteutukset osoittautuivat toimiviksi ratkaisuiksi. Sähkölämmitysmallin avulla käyttäjän on mahdollista optimoida lämmityskustannus ottaen huomioon tunneittainen tavoitelämpötila asunnossa. Kehitetty malli osoitti, että kuluttajien yhteistyö on mahdollista sähkön hankinnassa. Suomen ympäristökeskus hyödynsi vesistön säännöstelytehtävän mallia todellisessa säännöstelyn suunnittelussa ja arvioinnissa. Prosessiteollisuuden energiahallinnan tehtävässä hintakoordinointimenetelmä tuotti tehtävälle ratkaisun nopeasti, vaikka koordinointimenetelmän konvergenssia ei yleisesti voidakaan todistaa.

Avainsanat dynaaminen monitavoiteoptimointi, kaksitasoinen optimointi, hintakoordinointi, sähkön kulutuksen ohjaus, lämmityksen optimointi, sähkömarkkinat, vesistöjen säännöstely, energianhallinta prosessiteollisuudessa

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Contents

List of papers

This doctoral dissertation consists of this summary and the following papers:

Paper 1. Mäntysaari, J., and Hämäläinen, R. P. (1997). Prototyping customized DSS with a spreadsheet program - the power agents system. Journal of Decision Systems, 6(4), 391-402.
doi: 10.1080/12460125.1997.10511736.

Paper 2. Hämäläinen, R. P., Mäntysaari, J., Ruusunen, J., and Pineau, P-O. (2000). Cooperative consumers in a deregulated electricity market - Dynamic consumption strategies and price coordination. Energy - The International Journal, 25(9), 857-875.
doi: 10.1016/S0360-5442(00)00024-4.

Paper 3. Hämäläinen, R. P., and Mäntysaari, J. (2002). Dynamic multi-objective heating optimization. European Journal of Operations Research, 142(1), 1-15.
doi: 10.1016/S0377-2217(01)00282-X .

Paper 4. Hämäläinen, R. P., and Mäntysaari, J. (2001). A dynamic interval goal programming approach to the regulation of a lake-river system. Journal of Multicriteria Decision Analysis, 10(2), 75-86.
doi: 10.1002/mcda.290

Paper 5. Hadera, H., Ekström, J., Sand, G., Mäntysaari, J., Harjunkoski, I., and Engell, S. (2019). Integration of production scheduling and energy-cost optimization using mean value cross decomposition. Computers and Chemical Engineering, 129, 106436.
doi: 10.1016/j.compchemeng.2019.05.002.

Author's contribution

Paper 1. Prototyping customized DSS with a spreadsheet program - the power agents system

Mäntysaari was the main author and in charge of the development and implementation of the space heating model as well as writing of the article. Hämäläinen initiated and designed the research topic and contributed to the writing of the paper.

Paper 2. Cooperative consumers in a deregulated electricity market - Dynamic consumption strategies and price coordination

Mäntysaari constructed and implemented the price coordination model and conducted the numerical simulations. He wrote the descriptions of the model and the simulation results in the paper. Hämäläinen and Ruusunen were the initiators and the main researchers in the project. Hämäläinen and Ruusunen contributed to the writing of the paper. Pineau contributed to the writing of the introduction of the paper.

Paper 3. Dynamic multi-objective heating optimization.

Mäntysaari was the main author and responsible for the development of the space heating model, the GPϵ multiobjective optimization method and the proof for the method's capability to produce Pareto optimal solutions. Mäntysaari also implemented the spreadsheet prototype and conducted the numerical simulations. Mäntysaari was responsible for the main part in writing the paper. Hämäläinen formulated the research topic and contributed to the writing of the paper.

Paper 4. A dynamic interval goal programming approach to the regulation of a lake-river system

Mäntysaari formulated the lake-river model as well as developed the interval goal programming and rolling horizon approaches. Mäntysaari also carried out the spreadsheet implementation and the simulations. Mäntysaari was responsible for the main part in writing the paper. Hämäläinen formulated the research topic and contributed to the writing of the paper.

Paper 5. Integration of production scheduling and energy-cost optimization using mean value cross decomposition

Mäntysaari suggested the basic idea of the price coordination approach. He also contributed to the formulation of the minimum-cost flow network model as well as to the writing of the paper. Hadera was the principal researcher and author supported by Ekström, Sand, Harjunkoski and Engell.

Preface

My doctoral dissertation has been quite a lengthy journey. I began in the Systems Analysis Laboratory as a master's thesis worker back in 1995 and continued after graduating in 1996 as a doctoral student until my transition to the industry in 2000. I am grateful to Professor Emeritus Raimo P. Hämäläinen and Docent Jukka Ruusunen for initiating this research line well before energy management and the concept of time-varying electricity pricing became more common standards. I am very thankful for all the continued guidance from Raimo during the finalization of my dissertation. I wish to express my gratitude to Professor Carlos Henggeler Antunes and Doctor Jussi Hakanen for their positive pre-examination comments, which led to improvements in this dissertation.

At present, the university where I initially started has already undergone a name change, and my former graduate student fellow, Kai Virtanen, has now served as my supervising professor. I am very grateful to Kai for all the excellent instructions and support. I appreciate the ABB Oy as a company for providing me with both contacts and time to complete this dissertation. I would like to especially extend thanks to Doctor Hubert Hadera for our co-operation on the joint article.

I remember with longing my late parents, Seija and Matti, as they always respected my choices. I would also like to express my gratitude to my stepfather Teuvo and godfather Anders for always being there to help and support me in times of need.

Lastly, and most importantly, I owe my deepest gratitude to my love and wife, Eeva. You have inspired me with your own achievement of a doctoral degree. You have always encouraged me to follow my own path, and your support and belief in me carried me throughout this entire process.

Helsinki, August 12, 2023
Juha Mäntysaari

1. Introduction

Today, the increased requirements for efficiency and improved management practices in environmental and energy problems often lead to dynamic multiobjective optimization models. One needs to consider the changing demand and coordinate the production and use of energy accordingly, or one needs to optimize the regulation of river flows to sustain energy production and at the same time avoid flooding. This dissertation focuses on modeling challenges where these dynamic effects are met. Typically, there are no off-the-shelf solutions to these problems, but the solution methods need to be customized in each particular case.

This dissertation develops approaches to a number of such dynamic multiobjective optimization problems. These include the multiobjective optimization of an electrically heated house with an hourly varying price of electricity. This model is extended to the wider context of an electricity market by considering a coalition of cooperative space heating consumers aiming to optimize their total welfare by designing a within coalition time-of-use tariff. The dynamic regulation of a lake-river system is described by optimizing multiple objectives with interval goals and constraints. An industrial problem emerging from the combined production planning and energy supply is also considered.

The dynamic multiobjective problems studied here consist of three parts. First, there is a model describing the dynamics of the system. Second, the goals and the user's preferences are determined to define the objectives to be optimized. Finally, the solution approach and algorithm are developed. The challenge is to tackle all of these three parts so that the numerical solution will be practical and implementable in real life situations. These kinds of challenges emerge often in industrial problems but they are not typically discussed in the literature on multiobjective optimization.

In this summary, the approaches introduced in the dissertation are reflected against methods presented in the more recent literature. This summary article is structured as follows. Section 2 presents the methodological background of the dissertation. Section 3 discusses the results of Papers 1-5. Section 4 concludes by summarizing the contributions of the dissertation and discusses possibilities for future research.

2. Methodological background

The following chapters provide short introductions to the literature on the basic concepts and methods used in the dissertation. The more recent modeling efforts in the application areas considered in the dissertation are also summarized.

2.1 Multiobjective optimization

A multiobjective optimization problem can be defined as

$$\underset{\boldsymbol{x}}{\text{Minimize}} \{ f_1(\mathbf{x}), f_2(\mathbf{x}),..., f_k(\mathbf{x}) \}$$

subject to

$$\mathbf{x} \in S = \{ g_j(\mathbf{x}) \leq 0, j = 1,..., M \},$$

where the objective functions are $f_i(\mathbf{x})$ and $\mathbf{x}$ is the n-dimensional decision variable. The constraint functions $g_j(\mathbf{x})$ define the decision space S and a point $\mathbf{x}$ belonging to the decision space is called a feasible solution of the problem. The vector $\mathbf{z} = \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}),..., f_k(\mathbf{x}))$ related to a single solution is called an objective or criterion vector. In maximization, the problem definition applies similarly using negation of the objective functions, i.e., $-f_i(\mathbf{x})$. All objective and constraint functions are typically assumed to be convex and continuously differentiable to guarantee the existence of solutions.

2.1.1 Solution concepts

In a multiobjective problem, there is typically not a single best solution over all the objectives. The solution methods for multiobjective optimization problems aim to produce a set of nondominated solutions that are also called noninferior, efficient or Pareto optimal solutions. A solution is Pareto optimal, if none of the objective functions can be improved without degrading at least one of the other objectives. In other words, the solution is Pareto optimal when an improvement in one objective would lead to a weakening in at least one other objective. Formally, a solution $\mathbf{x}^p$ is Pareto optimal, if there does not exist another feasible solution $\mathbf{x}'$ that dominates it, i.e.,

$$f_i(\mathbf{x}') \leq f_i(\mathbf{x}^p) \text{ for all } i \in \{1,\dots, k\} \text{ and}$$
$$f_j(\mathbf{x}') < f_j(\mathbf{x}^p) \text{ for some index } j \in \{1,\dots, k\}.$$

The solution $\mathbf{x}^{wp}$ is called weakly Pareto optimal, if there does not exist another solution that is better with respect to each objective function, i.e., there does not exist another feasible solution $\mathbf{x}'$ such that $f_j(\mathbf{x}') < f_j(\mathbf{x}^{wp})$ for all $j \in \{1,\dots, k\}$. The set of all Pareto optimal solutions is called the Pareto set and the set of all Pareto optimal objective vectors is called the Pareto frontier. The decision maker, i.e., the owner of the multiobjective problem, is assumed to be rational in the sense of selecting the final solution from the set of Pareto optimal solutions.

The mapping of feasible solutions to multidimensional objective function values is called the objective function space Z. The space Z is often characterized by so called Ideal $\mathbf{z}^*$ and Nadir points, see, e.g., Miettinen (1999) and Antunes et al. (2016). The Ideal point $\mathbf{z}^*$ refers to the point defined by the values obtained by minimizing each objective function separately. The Nadir point $\mathbf{z}^{nadir}$ refers to the upper bounds of the objective functions on the Pareto frontier. The Ideal and Nadir points provide the range of Pareto optimal objective values for the decision maker to consider. The Ideal and Nadir points can be used to normalize the objective functions to a common scale in order to avoid numerical difficulties in optimization. In a higher dimension ($k > 2$), computing the true Nadir point is a difficult task on its own, since it requires knowledge of all the Pareto solutions.

The approximation of the Nadir point starts from calculating each single objective optimization separately to produce the Ideal point. The approximated Nadir point is formed by taking the worst value for each objective separately over all single objective optimizations. Figure 1 illustrates the Ideal and Nadir points in a two dimensional case.

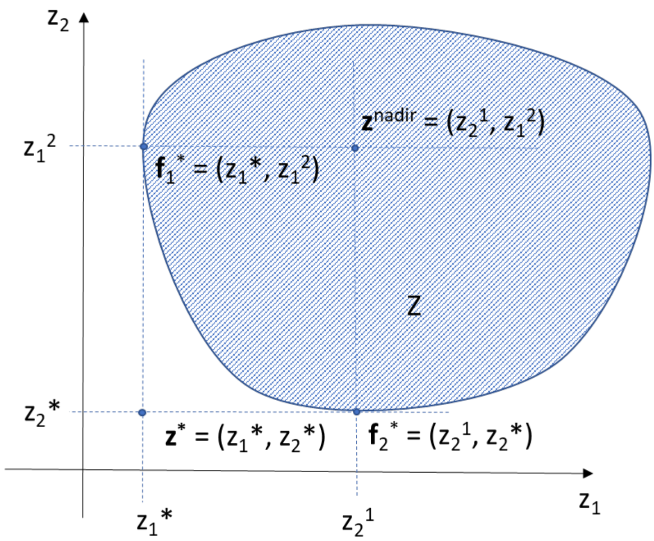


Figure 1. Ideal $\mathbf{z}^*$ and Nadir $\mathbf{z}^{nadir}$ points in a two-dimensional case. z_1^* and z_2^* are the optimal objective values for the first and the second objective, respectively. The Ideal point $\mathbf{z}^*$ is the combination of these. The Pareto frontier is the line segment between points **f**1* and **f**2*. The Nadir Point $\mathbf{z}^{nadir}$ is the upper bound of the objective values with respect to the Pareto frontier.

2.1.2 Solution methods

The solution methods for multiobjective optimization can be classified according to the availability of the decision maker's preference information, see, e.g., Miettinen (1999). There are no-preference, a priori, a posteriori and interactive methods. In the no-preference methods, a solution without preference information is generated, e.g., by minimizing the solution's distance to the ideal point. In a priori methods, the decision maker is first asked about preference information, such as the preferred values for each of the objective functions, and a solution closest to these values is generated. In a posteriori methods, a subset of the Pareto frontier is generated by converting the multiobjective function to a scalar objective function. This scalarization can be done typically with stated preference information. The decision maker is asked to choose a solution from of this subset of Pareto solutions generated. In interactive methods, the decision maker chooses a solution from the Pareto frontier in an interactive manner by stating desirable changes to the current objective vector. In this dissertation, the methods used mainly belong to a priori methods where stated preferences are ideal levels of indoor temperature and water reservoirs. In the following, typical methods in each of these classes are briefly described.

2.1.2.1 No-preference methods

In no-preference methods, a Pareto solution is generated directly without asking for any preference information. This is carried out, e.g., by minimizing the solution's distance to the Ideal point $\mathbf{z}^*$ using a suitable norm for the distance. An example norm is absolute deviation between an Ideal point $\mathbf{z}^*$ and an objective function space point $\mathbf{z} = (f_1(\mathbf{x}), f_2(\mathbf{x}),..., f_k(\mathbf{x}))$, i.e.,

$$\underset{\boldsymbol{x}}{\text{Minimize}} \ \sum_{i=1}^{k} |f_i(\boldsymbol{x}) - z_i^*| \text{ subject to } \mathbf{x} \in S.$$

This minimization problem gives a Pareto optimal point, see, e.g., Miettinen (1999). Different Pareto solutions can be generated using alternative norms, such as Euclidean second order or Chebyshev infinity order norms. Note that the minimization of the norm can be sensitive to the scaling of the objective functions, i.e., depending on the scaling used resulting solutions can differ considerably.

2.1.2.2 A priori methods

In a priori methods, the idea is to convert the multiobjective optimization problem back into a single objective optimization problem with the use of a scalarizing function. Typical scalarization methods include weighting (Gass and Saaty 1955), constraint methods (Chankong and Haimes 1983) and goal programming (Charnes et al. 1955). In the weighting method, the objective functions are associated with nonnegative weighting coefficients w_i to convert the problem into a single objective problem

$$\underset{\boldsymbol{x}}{\text{Minimize}} \; f(\mathbf{x}) = \sum_{i=1}^{k} w_i f_i(\boldsymbol{x}) \text{ subject to } \mathbf{x} \in S, \sum_{i=1}^{k} w_i = 1, w_i \geq 0.$$

The solution of the weighting method is Pareto optimal, if a nonzero weight is given for each objective, see Miettinen (1999).

In the constraint method, all but one of the minimized objective functions are constrained with given bounds c_i:

$$\underset{\boldsymbol{x}}{\text{Minimize}} \; f_j(\mathbf{x}) \text{ subject to } f_i(\mathbf{x}) \leq c_i, \; i \in \{1, 2, \ldots, j\text{-}1, j\text{+}1, \ldots, k\}$$

This minimizes one objective function and states strict bounds for the other objective functions. The decision maker states preferences by giving the bounds c_i for the other objective functions. In general, the constraint method generates weakly Pareto optimal solutions, but if the solution is unique it is also Pareto optimal, see Miettinen (1999). Different Pareto solutions can be generated by varying the weights or the bounds set to the objectives.

Goal programming is a widely used multiobjective optimization method. In this method, one minimizes the solution's distance to a given goal point for the objectives. The goal point $\mathbf{z}^{goal} = (z_1^{goal}, z_2^{goal}, \ldots, z_k^{goal})$ represents the desirable values of the objective functions. One such an example is the Ideal point $\mathbf{z}^*$. Here, the decision maker states preferences by the giving goal points. In many cases, the goal selected is unachievable.

The resulting weighted goal programming problem assuming unachievable goals is

$$\underset{\boldsymbol{x}}{\text{Minimize}} \; \sum_{i=1}^{k} w_i d_i$$

$$\text{subject to}$$

$$f_i(\mathbf{x}) - d_i \leq z_i^{goal},$$

$$d_i \geq 0, \mathbf{x} \in S,$$

where d_i are positive deviations from the goals of the objective functions, and w_i are nonnegative weighting coefficients. This problem produces a Pareto optimal solution, if all deviations from the goal point are strictly positive, i.e., the goal point cannot be achieved (Miettinen 1999).

A different distance measure is used in the achievement scalarizing function method (Wierzbicki 1982, Steur and Choo 1983). This method allows even achievable goal points, i.e., the $\mathbf{z}^{goal}$ point can belong to the objective function space Z. Formally, the method uses a distance measure

$$\underset{\boldsymbol{x}}{\text{Minimize}} \; max_{i=1,\ldots,k}\{w_i(f_i(\boldsymbol{x}) - z_i^{goal})\} + \rho \sum_{i=1}^{k} \left(w_i(f_i(\boldsymbol{x}) - z_i^{goal})\right)$$

$$\text{subject to } \mathbf{x} \in S,$$

which can have also negative value. Here, w_i are positive weights similarly as in the weighting method, and ρ is a small positive scalar. This method produces so called $\in$-Pareto optimal solution. A solution $\mathbf{x}^{\in p}$ is $\in$-Pareto optimal, if there exists no another feasible solution $\mathbf{x}'$ with given $\in > 0$ so that

$$f_i(\mathbf{x}') \leq f_i(\mathbf{x}^{\in p}) - \in \text{ for every } i \in \{1,\ldots, k\} \text{ and}$$
$$f_j(\mathbf{x}') < f_j(\mathbf{x}^{\in p}) - \in \text{ for some } j \in \{1,\ldots, k\}.$$

The goal can also represent a goal set, such as an interval goal, see, e.g., Romero (2019) and Oliveira and Antunes (2007). The goal interval states lower and upper bounds for the objective function instead of a single value. For a more general overview of goal programming, see Jones and Tamiz (2010). Goal programming has continued its popularity in many engineering and management problems, see, e.g., the survey by Colapinto et al. (2017). Many other possible forms of scalarization functions using goal points also exist, see, e.g., Miettinen and Mäkelä (2002).

2.1.2.3 A posteriori methods

In a posteriori methods, first multiple Pareto optimal solutions are generated. After a representative part of the Pareto optimal solutions is generated, they are presented to the decision maker from which he or she chooses the preferred one. A difficulty is that how to present a large set of alternative solutions to the decision maker. Scalarizing methods can be considered as one category of a posteriori methods. Multiple Pareto solutions are obtained by changing preference parameters, such as the weights of the objectives or the goal points. More recently population based methods, such as genetic algorithms, have gained interest in a posteriori methods (Deb 2001, Li et al. 2015, Azzouz et al. 2017) because of their capability to produce multiple solutions simultaneously. Genetic algorithms are inspired by natural selection of the fittest, see, e.g., Tang et al. (2012). In these algorithms, candidate solutions for the multiobjective problem are encoded and evaluated with objective functions in each iteration. Candidate solutions are chosen to a mating pool based on their associated overall fitness value. The entire pool is then exposed to a number of genetic operations, such as crossover, to combine solutions into a new candidate solutions. A randomization operation produces random alterations to candidate solutions called mutations. These operations try to find a balance between exploring for unknown better solutions and improving the solutions found so far. These phases are then repeated until the stopping condition of an algorithm is satisfied. The stopping condition can be, e.g., the maximum number of generations. However, the solutions obtained using genetic algorithms are not generally true Pareto optimal solutions, but points close to the actual Pareto optimal solutions (Deb 2001). A well known genetic algorithm is the non-dominated sorting genetic algorithm (NSGA-II) for problems with two or three objectives, see Deb et al. (2002). The method has been extended to the so called NSGA-III algorithm (Deb and Jain 2014) and unified NSGA-III (Vesikar et al. 2018) which are more efficient in solving problems with a higher number of objectives. Another multiobjective evolutionary algorithm is MOEA/D, which is based on decomposing a multiobjective problem into a number of single objective problems and solving them simultaneously. The single objective problems are solved using information from solutions of neighboring problems during the execution of algorithm (Zhang and Li 2007).

2.1.2.4 Interactive methods

There are also interactive approaches for multiobjective optimization, see, e.g., Miettinen et al. (2016), Antunes et al. (2016), and Xin et al. (2018). Interactive methods typically start by presenting one initial Pareto optimal solution to the decision maker. The decision maker is then asked to provide some preference information. This can be done, e.g., by asking her to allocate the objectives in different categories. These categories could define, e.g., objectives which should be decreased, objectives which are satisfactory, or objectives which can be allowed to increase, with respect to the current solution, see, e.g., Sindhya et al. (2014). New solutions are generated using this preference information. An approach is to add constraints with respect to the current solution to force the solution into directions given by the decision maker. The new solution then replaces the current solution. This process is repeated until the decision maker is satisfied with the solution.

The motivation for using interactive methods is that initially the decision maker might not have clear preferences over Pareto optimal points. By interactively exploring the Pareto frontier more knowledge is gained. Interactive methods reduce the number of Pareto solutions that decision maker needs to consider. This aspect can be relevant especially in complex real life problems.

2.1.3 Solution methods used in the dissertation

Solutions methods considered in this dissertation are based mainly on constraint, weighted goal programming and interval goal programming methods. The dissertation develops an interval goal programming method with multiple intervals and points out that in dynamic optimization problems the goals of the objective functions might be time dependent. The dissertation formulates also a combined method of a constraint method and goal programming.

In Paper 3, goal programming is combined with a constraint method. In this method, original objective functions are classified into a constraint set E and a goal set G. For objective functions in the constraint set, hard upper bounds c_j are given. On the other hand, only goal values z_i^{goal} for objective functions in the goal set are stated. The deviations from the goals are minimized. In this way, the original multiobjective optimization problem is converted into the form

$$\underset{\boldsymbol{x}}{\text{Minimize}} \ \sum_{i \in G} w_i d_i$$

subject to

$$f_i(\mathbf{x}) - d_i \leq z_i^{goal},\ d_i \geq 0,\ \forall\, i \in G,$$

$$f_j(\mathbf{x}) \leq c_j,\ \forall\, j \in E,$$

$$\mathbf{x} \in S.$$

The combined constraint and goal programming method is illustrated in Figure 2 in a two dimensional case. The first objective is given a hard upper bound c_1, while the second objective is associated with an unachievable goal z_2^{goal}. The optimal solution for the combined problem formulation provides in this case a Pareto solution z* with deviation d_2 from the goal of the second objective. Other Pareto solutions could be produced by making the upper bound restriction for the first objective smaller, i.e., more constraining.

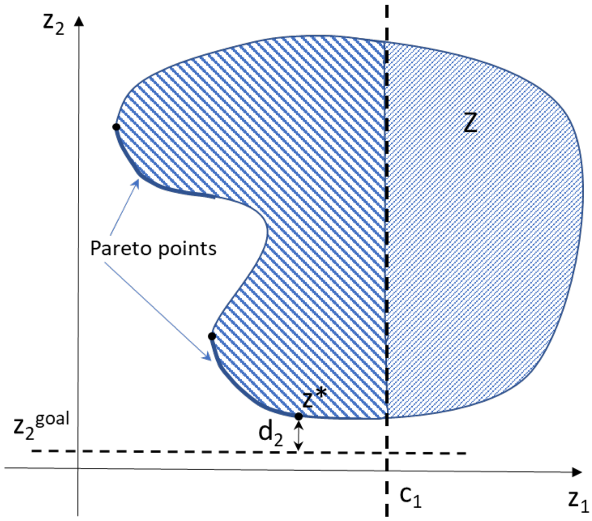


Figure 2. Illustration of the combined goal programming and constraint method. The objective function space is Z. The axes z_1 and z_2 are the objective function values for the first and second objective, respectively. The constant c_1 is the hard upper bound for the first objective, and z_2^{goal} is an unachievable goal for the second objective. z* is the Pareto optimal solution with d_2 being the deviation to the goal for the second objective.

In Paper 3, the Pareto optimality of the solution for the problem formulation above is proven under an assumption that there is only a single optimal solution. The combined goal programming and constraint method is used in Paper 3 for solving a multiobjective house heating problem. House heating costs and heating energy are turned into hard constraints, while minimal indoor temperature discomfort remains as a goal.

In Papers 1, 3, and 4, the interaction with the decision maker is based on asking the decision maker's goals and constraints for variables describing a system under consideration at different time points. In the applications addressed in this dissertation, the dynamics of problems originate on the one hand from the characteristics of systems in question, i.e., the heat capacity and dissipation in the house in Paper 1 and 3, and the geographical form of lakes and rivers in Paper 4. On the other hand, these problems also have external dynamics due to the time-varying price of electricity and the time-varying inflow of water.

In the house heating problem, the goal level for indoor discomfort is defined by stating desired hourly temperatures in the house, and in the river management case the interaction with the decision maker is based on lake water levels at different days of a planning period. The resulting optimal solution is presented and visualized to the decision maker after which the decision maker is allowed to adjust the goals of the system states to find a more desirable solution. This is repeated until a satisfactory solution is found. Thus, the method used can be called an interactive goal programming.

2.2 Dynamic multiobjective optimization

The dynamics in multiobjective optimization problems can be due to a number of factors including time varying objectives, constraints and parameters as well as due to the dynamics of the system being studied. Such a setting results in a continuous time dynamic optimization or optimal control problem. In practice, time is discretized making it possible to convert the problem into a standard form of a multiobjective optimization problem. This introduces vector of decision variables for each time discretization point $\mathbf{x}(t_I) = \mathbf{x}_I$, I = 1,...,N. The entire decision vector containing all time discretization points $t = (t_1,...,t_N)$ is denoted by $\mathbf{x}(t)$. The same applies for dynamic parameters affecting the objective functions. That is for each objective function, there is a parameter vector at each time discretization point $\mathbf{w}_i(t_I) = (\mathbf{w}^i_1(t_I),..., \mathbf{w}^i_{Ki}(t_I))$, where K_i is the number of parameters of objective function i. The entire parameter vector containing all time discretization points for the object function i is denoted by $\mathbf{w}_i(t)$, i = 1,...,k. The formal formulation of this problem is

$$\underset{\boldsymbol{x}(t)}{\text{Minimize}}\{f_1(\mathbf{x}(t), \mathbf{w}_1(t)), f_2(\mathbf{x}(t), \mathbf{w}_2(t)),..., f_k(\mathbf{x}(t), \mathbf{w}_k(t))\}$$

$$\text{subject to}$$

$$\mathbf{g}(\mathbf{x}(t)) \leq 0,$$

$$\mathbf{x}(t) \in S,$$

where the constraints are $\mathbf{g}(\mathbf{x}(t))$, and S defines lower and upper limits of the decision variables.

In electricity market models introduced in Papers 1, 2, and 3 of this dissertation, the time dependent parameter represents the time varying price of electricity. In the lake-river regulation models elaborated in Paper 4, the parameters are related to the inflow of water at different times. A quite similar model with dynamic goals is found, e.g., in the health-care related dietary menu planning problem studied by Jridi et al. (2018).

The house heating problem of the home owner developed in Paper 3 is used here to illustrate the above general formulation of a dynamic multiobjective problem with a dynamic goal programming approach. The problem has two objectives, i.e., minimization of the total heating costs over the day and maximization of the living comfort, which is converted to minimization of living discomfort. The measure used for the loss of living comfort is the temperature deviation from the ideal indoor temperature. In this case, the time dependent parameters are electricity prices and outdoor temperatures. The discrete time index is i = (1,...,N) as in Paper 3, and N is the number of discretization points. The dynamics of the problem are related to the heat dynamics of the house. The house acts as an energy storage, and heat flow out of the house is assumed to depend linearly on the difference between the indoor and outdoor temperatures. The heating problem for a cyclic period, such as one day, is

$$\underset{\boldsymbol{q}(t)}{\text{Minimize}} \text{ (heating costs)} \quad f_1(\mathbf{q}(t), \mathbf{p}(t)) = \textstyle\sum_i p_i q_i$$

$$\underset{\boldsymbol{T}(t)}{\text{Minimize}} \text{ (discomfort)} \quad f_2(\mathbf{T}(t), \mathbf{T}^{ref}(t)) = \textstyle\sum_i |T_i - T_i^{ref}|$$

$$\text{subject to}$$

$$T_{i+1} = T_i + \beta\Delta t q_t - \alpha\beta\Delta t(T_i - T_i^{out}) \quad \text{(Heat dynamics of the house),} \qquad (1)$$

$$T_1 = T_{N+1} \quad \text{(Periodicity of the indoor temperature),}$$

$$0 \leq q_i \leq q \quad \text{(Heating power limits),}$$

$$l_i \leq T_i \leq u_i \quad \text{(Indoor temperature limits),}$$

where T_i is the indoor temperature, T_i^{ref} is the ideal indoor temperature for the decision maker, and T_i^{out} is the outdoor temperature at time i, respectively. The q_i represents the heating power and p_i price of the electricity at time i. The time difference between the discretization points is Δt. The initial indoor temperature T_1 and the end temperature T_{N+1} are constrained to be the same to ensure the cyclic behavior of indoor temperatures. The lower and upper limits for the indoor temperature are denoted by l_i and u_i. The maximum heating capacity q is here constant over time. The heat dissipation coefficient of the house is α, and the inverse of the heat capacity of the house is β.

The solution approaches to discrete time dynamic multiobjective problems are based on the same ideas as for the static multiobjective problems. The dynamic goal programming approaches used in Paper 1, 3, and 4, are extensions of the static ones. For instance, the combined goal programming and constraint method developed in Paper 3 can be applied to the house heating problem. The first objective function f_1 of Problem (1) is the heating costs of the house. The minimal heating costs of the house, when thermodynamical and heating power limitations are only considered, is denoted by f_1^*. Additionally, the goal level for the heating costs is parameterized with constant eps, where $0 \leq eps < 1$. The minimal discomfort level, i.e., the objective function f_2 in Problem (1), would be zero for obvious reasons. Deviation from that can be measured and is denoted by d. This gives a combined goal programming and constraint method problem as

$$\underset{\boldsymbol{q}(t), \boldsymbol{T}(t), d}{\text{Minimize}} \ d$$

$$\text{subject to}$$

$$f_1 \leq (1-eps)f_1^* \quad \text{(Constraint for heating costs),}$$

$$f_2 - d \leq 0 \quad \text{(Goal for discomfort),}$$

$$d \geq 0 \quad \text{(Deviation from minimal discomfort),}$$

$$T_{i+1} = T_i + \beta\Delta t q_t - \alpha\beta\Delta t(T_i - T_i^{out}),\ T_1 = T_{N+1} \quad \text{(House dynamics),}$$

$$0 \leq q_i \leq q,\ l_i \leq T_i \leq u_i \quad \text{(Heating and indoor temperature limits).}$$

In practical problems, time varying parameters can be affected by uncertainties. Such a case in the lake regulation problem of Paper 4 is due to uncertain water inflow forecasts to the lake-river system. The idea of a rolling horizon solution approach used here is that the dynamic goal programming problem is solved repeatedly. Goals are set ahead of time for a rolling time window as illustrated in Figure 3. In practice, this means solving the dynamic goal programming problem whenever the rolling time period is changed. This kind of approach has also been called a myopic solution approach in Virtanen et al. (2004).

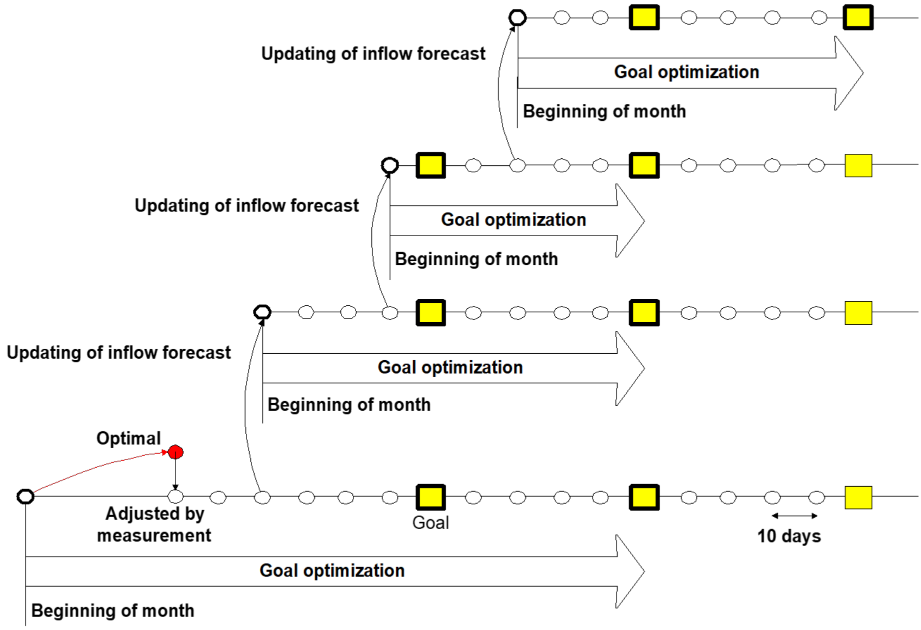


Figure 3. Solution of the dynamic goal programming problem using the rolling time horizon approach.

In general, the introduction of dynamics brings complexities as the problem size can increase essentially, which in turn makes it more difficult to generate efficient solutions (Farina et al. 2004, and Helbig et al. 2016). The increase in problem size with a high number of decision variables also makes interactive approaches difficult to use. Yet, interest in dynamic multiobjective problems has been increasing and new approaches have been suggested based on, e.g., genetic algorithms (Raquel et al. 2013) and evolutionary techniques (Deb et al. 2007, Helbig and Engelbrecht 2014, and Orouskhani et al. 2019). New interactive approaches have also been developed by focusing on only part of the possible Pareto solutions directly by using the decision maker's preference knowledge (Nowak and Trzaskalik 2021, and Aghaei Pour et al. 2021). For a recent extensive survey on dynamic multiobjective optimization, see Jiang et al. (2022).

The importance of dynamic problems is emphasized in the reviews of Helbig and Engelbrecht (2014) and Helbig et al. (2016). However, the survey of Azzouz et al. (2017) suggests that so far there are still only a few real-world applications of dynamic multiobjective optimization models.

2.3 Bi-level optimization and price coordination

In bi-level optimization problems, the lower level optimal reactions to upper level decisions appear as constraints for the upper level optimization. For a general introduction to bi-level optimization, see, e.g., Talbi (2013) and Dempe et al. (2015). A bi-level optimization problem is of the form

$$\underset{\boldsymbol{u},\boldsymbol{x}}{\text{Minimize}}\ f_L(\mathbf{u},\mathbf{x})$$

$$\text{subject to } \mathbf{g}_L(\mathbf{u},\mathbf{x}) \leq 0,$$

$$\mathbf{x} \in \text{argmin}\ \{\underset{\boldsymbol{x}}{\text{Minimize}}\ f_F(\mathbf{u},\mathbf{x}) \text{ subject to } \mathbf{g}_F(\mathbf{u},\mathbf{x}) \leq 0\}.$$

The upper level's decision variable vector **u** affects the lower level reactions **x**. The function f_L is the objective function of the upper level (leader), and $\mathbf{g}_L$ represents the constraints of the upper level. The f_F is the objective function of the lower level (follower), and $\mathbf{g}_F$ is the constraints functions of the lower level. The solution methods for bi-level optimization usually assume that the upper level optimization can be carried out under the knowledge of the objective of the lower level problem. Bi-level optimization problems are computationally difficult to handle, and they can be hard to solve even in a simple case with linear objective and constraint functions (Ben-Ayed and Blair 1990). The solution methods for bi-level optimization can be based on reducing the original bi-level problem into one larger single level problem. This can be done under a suitable convexity and the assumptions of constraint qualification. One such a method is adding the Karush-Kuhn-Tucker optimality conditions of the lower problem into the upper level problem as constraints using Lagrangian and complementary constraints, see, e.g., Dempe (2020). This is stated as

$$\underset{\boldsymbol{\lambda},\boldsymbol{u},\boldsymbol{x}}{\text{Minimize}}\ f_L(\mathbf{u},\mathbf{x})$$

$$\text{subject to}$$

$$\mathbf{g}_L(\mathbf{u},\mathbf{x}) \leq 0,$$

$$\mathbf{g}_F(\mathbf{u},\mathbf{x}) \leq 0,$$

$$\nabla_x f_F(\mathbf{u},\mathbf{x}) + \sum_i \lambda_i \nabla_x g_{Fi}(\mathbf{u},\mathbf{x}) = 0 \text{ (Lagrangian)},$$

$$\lambda_i\ g_{Fi}(\mathbf{u},\mathbf{x}) = 0,\ \lambda_i \geq 0,\ i = 1,\dots, M \text{ (Complementary)},$$

where M is the number of constraint functions, λ_i are the Lagrangian coefficients, and ∇_x is the gradient with respect to lower level reaction **x**. Especially, in the case of linear objective and constraint functions, the complementary constraints can be solved by transforming the problem into a mixed integer linear optimization problem by using the so-called big-M method. This can be accomplished by replacing the complementary constraint with the constraint

$$\lambda_i \le M_{big}\, y_i \text{ and } g_{Fi}(\mathbf{u},\mathbf{x}) \le M_{big}\,(1-y_i),$$

where the binary decision variable $y_i \in \{0,1\}$ represents the activity of the lower level constraint, i.e., in case $y_i = 1$ the associated constraint is active $g_{Fi}(u,x) = 0$. The big-M constant (M_{big}) should be a sufficiently large constant for both Lagrangian coefficients λ_i and lower level constraints. This enables solving the above single level reformulation by using modern general purpose mixed integer linear programming solvers. However, the choice of the value M_{big} itself is a hard problem, see, e.g., Pineda and Morales (2019).

The scope of bi-level multiobjective problems is vast and has been constantly growing during the past years. This is pointed out in the extensive reviews of Lachhwani and Dwivedi (2018), Sinha et al. (2018) and Said et al. (2021). Bi-level optimization problems arise in many practical settings. For example, there can be an upper level actor/agent (e.g., a department, a manager or a leader) which optimizes its own objectives which depend on the performance of the lower level actors/agents (followers) which again have their own optimization objectives. For examples of different bi- and multi-level settings, see the survey by Lachhwani et al. (2018). Bi-level problems are typically also asymmetric so that the upper level has more information about the lower level's problem than the lower level about the upper level's. The Stackelberg game, which is common in pricing models (van Hoesel 2008), also results in a bi-level optimization problem. For a survey of price setting problems, see, e.g., Labbé and Violin (2016). In a price setting problem, the upper level sets the price of the service by taking into account the reactions of the customers on the lower level. The bi-level structure can also emerge from the decomposition of a larger problem into smaller ones. Optimization problems can contain nested inner optimization problems as constraints (Bracken and McGill 1973). Similar setups can be found, e.g., in Kuo et al. (2015).

Research on different hierarchical coordination methods was active in the 1970s in the field of control and systems theory dealing with the so-called large-scale systems, for a review, see Mahmoud (1977). Later the literature has focused on market type settings in different industries. Current interest in price based coordination is strong in the analyses of electricity markets (Tohidi et al. 2018). Price coordination is an approach in pricing problems where the price or tariff is iterated towards the optimal one by taking into account the reactions of the lower level agents which typically represent the customers.

In Papers 2 and 5 of this dissertation, the solution methods used for bi-level problems apply price coordination where the idea is to divide the solution process into the optimization of two simpler problems and to solve these iteratively. The upper level chooses a price for the lower level. The lower level reacts optimally to the price with the consumption decision. The reaction affects the value of the upper level's objective function. The upper level then updates the price signal in each iteration by re-optimizing against the reaction of the lower level. In Paper 2, this is realized by defining the a total welfare function U(q,p) for the coalition of electrical heating consumers. It is the sum of the utility function of a coalition coordinator $U_p(q,p)$ and the utility functions of individual consumer groups $U_j(q_j,p)$. Here, p is the price signal of the electricity, q_{jk} is consumption of the consumer group j, and q is the total consumption over all consumer groups. The coalition coordinator's cost in the Paper 2 is assumed to be quadratic with respect to consumptions of the consumer groups, and the utility function of the coordinator is the profit subtracted by cost. The consumer's utility function is a weighted sum of energy costs and degradation of living comfort. The entire price coordination scheme is illustrated in Figure 4.

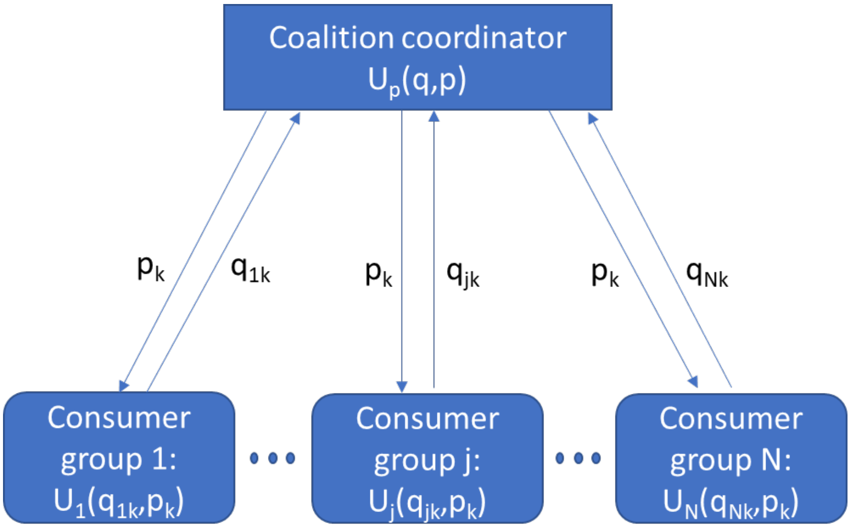


Figure 4. Price coordination scheme for the coalition of consumers in Paper 2. The lower level consumers determine their consumptions q_{jk} by maximizing their utility functions independently at each iteration k, and the upper level iterates the overall utility by updating the price signal p_k.

The total utility function U(q,p) depends on the consumptions of the individual consumer groups q_j, which on the other hand depend implicitly on price p. The iteration process is based on the marginal costs (mc) of the total welfare, which is a function of the sum of the individual consumptions q_j. The price iteration proceeds by updating the price using a weighted updating formula, i.e.,

$$p^{k+1} = \mu\, p^k + (1-\mu)\, mc^k(\textstyle\sum_j q_j),$$

where k is the iteration round, and μ is a small constant $0 \le \mu < 1$.

In Paper 5, combined production scheduling and energy management optimization problems are discussed for process industrial cases. Such problems are often large and hard to solve as a single problem. In Paper 5, the decomposition of the original combined production scheduling and energy management optimization problem is tackled with two well know decomposition methods, i.e., Benders and Dantzig-Wolfe decomposition methods.

The Benders decomposition (Benders 1962), also called primal decomposition, was first developed for large linear programming problems which have a special block structure with common constraints and independent sets of other constraints and variables. Stating a given values for the part of the variables of the common constraints of the original problem defines a primal subproblem. The primal subproblem is a function of the fixed common constraint variables. Each solution of the primal subproblem generates an extreme solution for the original problem, which can be used to add a new constraint, i.e., so called Benders cut, to the Benders master problem representing the original problem. The master problem yields another point of the fixed variables, and the iteration continues by forming a new primal subproblem with the current values of the fixed variables to generate a new extreme solution of the original problem. Therefore, the primal master problem iteratively approaches the original problem. It can be shown that the Benders subproblem provides an upper bound for the optimal value of the objective function of the original problem, and that the decomposition stops after a finite number of iterations, see, e.g., Holmberg (1994).

The Dantzig-Wolfe (Dantzig and Wolfe 1960) decomposition, also called dual decomposition, starts by dualization of common constraints. This means that penalties are given for the violations of the common constraints and the penalty term is added to the objective function of the original problem. Fixing the penalties, i.e., the dual variables of the common constraints, the solution of this dual subproblem generates an extreme solution for the original problem. This solution is used to add a new constraint to the Dantzig-Wolfe master problem representing the original problem. The solution of the master problem then gives new values of the dual variables, and the iteration is continued to a new subproblem to generate a new extreme solution. The master problem approaches the original problem with the addition of each new constraint. It can be shown that the Dantzig-Wolfe subproblem provides a lower bound for the optimal value of the objective function of the original problem, and that the decomposition stops after a finite number of iterations, see, e.g., Holmberg (1994).

The idea of the cross decomposition algorithm (Van Roy (1983), Holmberg (1992), and Holmberg (1997)) used in Paper 5 is to omit the need of master problems. The algorithm is based on iterating between the subproblems of the Benders and Dantzig-Wolfe decompositions. This cross decomposition algorithm is illustrated in Figure 5.

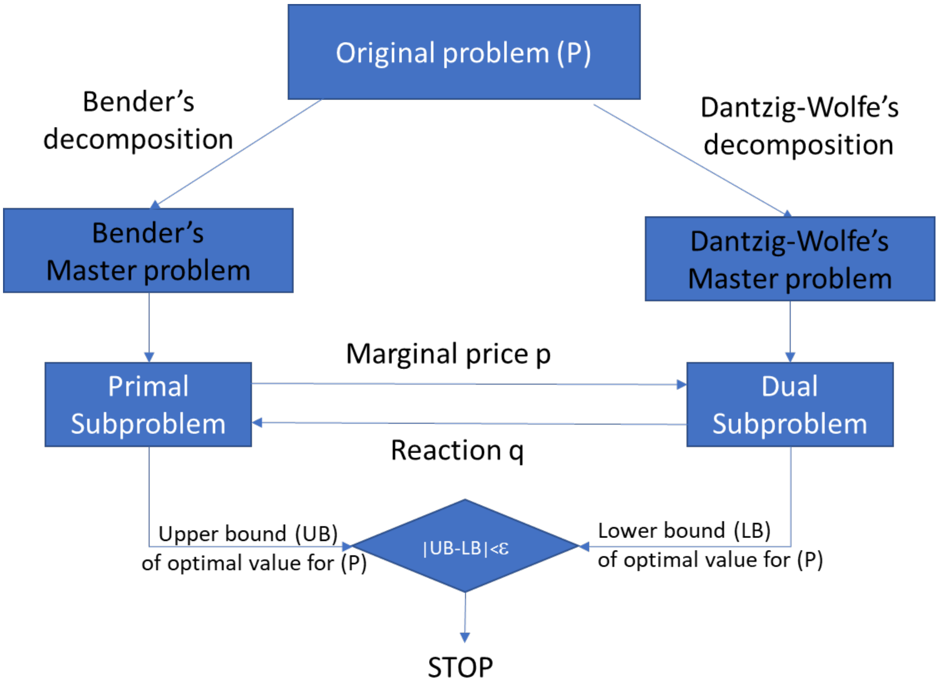
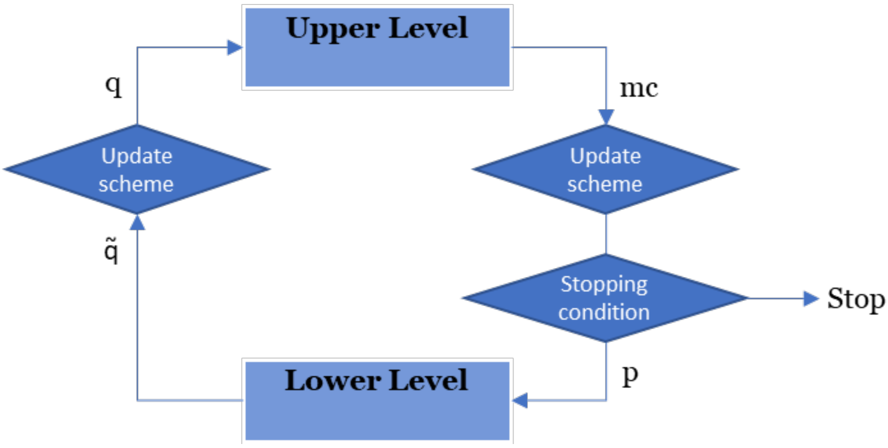


Figure 5. Cross decomposition algorithm. The marginal price p is the input to the dual subproblem and the reaction q is the input to the primal subproblem.

In the cross decomposition algorithm, the Bender's primal subproblem provides new values of dual variables, i.e., marginal prices, to be given to the Dantzig-Wolfe dual subproblem (see Figure 5). The solution of the Dantzig-Wolfe subproblem reveals a new fixed values of common constraint variables, i.e., reaction, to be given back to the primal subproblem. The marginal price and reaction are used as exchanged information called here as signals between the subproblems (Holmberg 1999). There can be multiple ways to adjust the price and reaction signals before giving them to subproblems according to previous values of these signals as illustrated in Figure 6 with four basic schemes. The heuristic scheme uses a direct passing of price and reaction without any changes. The mean value scheme updates both price and reaction as the mean values of the previous prices and reactions. The weighted mean value scheme is similar, but it gives less weight to the previous price and reaction values. The one sided weighted mean values scheme passes the reaction without change, but it uses weighted mean values updating for the price. The cross decomposition algorithm converges for a linear programming using either mean value scheme (Homberg 1994). The cross decomposition algorithm is proven to converge for a certain mixed integer linear programming problem under special block structure using the mean value coordination scheme for both price and reaction signals (Holmberg 1997).



Coordination scheme	Updating price and reaction
Heuristic (direct)	$q^k = \tilde{q}^k$, $p^k = mc^k$
Mean value	$q^k = (1/k)\, \tilde{q}^k + (k-1/k)\, q^{k-1}$, $p^k = (1/k)\, mc^k + (k-1/k)\, p^{k-1}$
Weighted mean value	$q^k = \delta_k\, \tilde{q}^k + (1-\delta_k)\, q^{k-1}$, $p^k = \delta_k\, mc^k + (1-\delta_k)\, p^{k-1}$
One sided weighted mean value	$q^k = \tilde{q}^k$, $p^k = \delta_k\, mc^k + (1-\delta_k)\, p^{k-1}$, where weight $0 < \delta_k < 1$

Figure 6. Different price coordination schemes. The marginal price mc from the upper level problem is updated to the price p signal, and the reaction $\tilde{q}$ from the lower level problem is updated to the reaction q signal.

In the industrial combined production planning and energy optimization problems in Paper 5, i.e., a thermo mechanical pulping planning in the pulp and paper industry and a stainless-steel production planning in the steel industry, a two level structure reflects a natural two-level settings with a producer and a consumer. The convergence of the cross decomposition algorithm using the one sided weighted mean value price coordination scheme to the optimal solution of the original combined problem is case dependent and no general convergence results exist in the current literature.

2.4 Applications of multiobjective approaches in house heating and river management

More than twenty years have passed since the publication of the initial papers in this dissertation. The topic has since proven to be of great importance. Multiobjective modeling has become widely known and applied in different application areas including, in particular, energy and environmental studies. This has resulted in an explosion of research papers in the areas, and a comprehensive survey of the relevant literature is not possible within the scope of this dissertation summary. However, key references to articles which reflect the development of the field are provided. Developments in the measurement, communication and computational technologies have also made the practical implementation and use of dynamic multiobjective methodologies and models attractive. Dynamic multiobjective approaches are increasingly important both in energy and environmental problems. Today, there is a strong interest in finding ways to change behavior in energy use, and these settings are typically dynamic and have multiple criteria (Lopes et al. 2020). The methodological development studied in this dissertation relates directly to the challenges met in the currently active research areas of smart cities, smart homes, intelligent energy use and smart grid, see, e.g., Kirimtat et al. (2020), Ringler et al. (2016), Xu et al. (2020).

2.4.1 House heating

The use of multicriteria optimization in house design originated early. Gero et al. (1983) and D'Cruz and Radford (1987), were among the first to consider multiple objectives in building design. Later the related literature has expanded rapidly and environmental sustainability criteria have also become important. For a recent survey, see, e.g., Gassar et al. (2021). The idea, in Papers 1 and 3, that the home-owner would be able to react to the electricity price by changing the indoor temperature is a different one than the optimization of the design of the house. Technically the resulting multiobjective problems can, however, become similar. The inclusion of hourly thermal comfort in a house heating model is considered in Paper 1 of this dissertation. Comfort is described as a time-varying ideal indoor temperature at different hours of the day. Cost and the sum of deviations from the ideal temperature are minimized subject to time-varying tariff and outdoor temperature. The model is developed further in Paper 3. These models are developed to support the house owner in choosing the hourly heating pattern. At the same time, a similar type of multiobjective model was developed by Wright et al. (2002) to support the design of the house. In their paper, the objectives included cost and thermal comfort and the optimization is done subject to time varying outdoor temperature but without a dynamic tariff.

There has also been interest in control models regarding multiobjective heating and ventilation strategies, see, e.g., Wright et al. (2002) and Ascione et al. (2019). These papers have considered buildings including residential units and schools. Ascione et al. (2016) have developed a control model for a home which has similar characteristics with user defined goals as in the papers in this dissertation. The control model of Álvarez et al. (2013) takes into account the comfort needs in different rooms of a house. The design of energy efficient homes and buildings by including comfort criteria remains of continuous interest. For example, Asadi et al. (2012) as well as Ascione et al. (2017) consider the retrofitting strategies of houses using multiple objective optimization. Yu et al. (2015) is another highly cited building design focused paper.

Today, the literature on intelligent buildings is extensive. Mofidi and Akbari (2020) provide a comprehensive review of factors such as thermal comfort to be considered in the multiobjective modeling approaches for intelligent buildings. The authors emphasize that in future models more emphasis should be paid to the occupant behavior and feedback possibilities to occupants, such as household energy consumption values. New energy management systems for buildings also have similar elements as the original home heating models in the dissertation. The system described in Pallante et al. (2020) can carry out day-ahead optimizations taking into account the building dynamics as well as hourly comfort and cost. The time frame can also be longer and seasonal strategies for different weather conditions can be optimized like in Ascione at al. (2019).

The optimization techniques used in building design applications vary. Wright et al. (2002), Hamdy (2012), Hirvonen (2017), Ascione et al. (2017) and Ascione et al. (2019) all use genetic algorithms to generate multiple Pareto solutions in one execution run of the algorithm. In their methods, penalties are sometimes used to avoid infeasible solutions. The objective function values are evaluated for the solution candidates using a simulation model for the building's energy performance. Gomes et al. (2007) also use genetic algorithms. Their evolutionary algorithm accommodates a progressive articulation of the decision maker's preferences by changing aspiration or reservation levels used in the fitness assessment of the individuals in the solution population. The inclusion of preferences in this manner may reduce the run time of the genetic algorithm substantially. Asadi et al. (2012) use the weighted Tchebycheff goal programming approach for generating Pareto solutions for the multiobjective problem. Yu et al. (2015) take a different approach and use an artificial neural network to approximate the building model trained with results from a building simulation model. The neural network model is then used in the multiobjective approach where the design variables of the building are optimized with respect to objectives representing energy costs and thermal discomfort. The Pareto frontier is obtained by using the non-dominated sorting genetic algorithm (NSGA-II). The paper by Pallante et al. (2020) also uses a simulation module for the building which generates the comfort and cost estimates and the number of unsatisfied people in the building. They too apply the NSGA-II method and compare it with the so-called surrogate method.

One can say that multiobjective house design is today a hot research area. New methods are continuously introduced and tested. One example is the recent paper by Chegari et al. (2021) which applies artificial neural networks and metaheuristic algorithms.

2.4.2 River Management

Water resources management has for long been an application area for multiobjective optimization (Haimes 1974, Duckstein and Opricovic 1980). The number of studies has grown extensively over the years and today there is a wide range of dynamic formulations too. Different versions of the goal programming method for the operation of reservoirs were studied early (Can and Houck, 1984, Eschenbach et al. 2001). Loganathan and Bhattacharya (1990) already note the possibility of using interval goal programming which is also used in Paper 4.

Many papers consider water reservoir management under uncertainty. The objectives considered in these models range from minimizing flood damages and energy optimization to social and ecological goals (Yan et al. 2020). The popularity of evolutionary and genetic algorithms is also strongly visible in this literature (Reed et al. 2013, Hojjati et al. 2018, Stretch and Adeyemo 2018). For example, Liu and Luo (2019) propose an interactive model which is solved with the genetic algorithms NSGA-II and MOEA/D. The optimization problems become difficult when whole river basins, rather than just one reservoir, are studied.

Multiobjective river flow management is also approached by multicriteria decision analysis where the solutions are sought interactively rather than by optimization, see, e.g., Vassoney et al. (2017). The ways decision processes are carried out with stakeholders need growing attention. There can be behavioral impacts both in the modeling stages and in the interaction and communication with the stakeholders which need to be taken into account (Hämäläinen 2015, Marttunen et al. 2015).

2.5 Bi-level optimization in electricity market models and in industrial energy management

2.5.1 Electricity markets

Today, there is a strong interest in analyzing cooperation of agents in the electricity markets by bi-level modeling. Such papers include, e.g., Alves et al. (2016), Siano et al. (2014) and Acuña et al. (2018). The review by Antunes et al. (2020) shows that the bi-level approach is relevant in many different settings and a variety of modeling and optimization methods are used. Soares et al. (2020) is an example of a new approach as they use particle swarm optimization for setting electricity prices in retail's upper level problem for lower level residential consumer groups. On the lower level, they apply an exact mixed integer linear optimization model. Their model contains residential thermostatic consumption behavior having a discomfort term associated with the resulting indoor temperatures. They also give suggestions for estimating the lower and upper bounds for the optimal value of the upper level's objective function. This is accomplished by using sup-optimal lower levels solutions, and by disregarding the discomfort term on the consumer's side.

The bi-level setting in Paper 2 is close to models that have a broker or an intermediary between the consumer and the electricity market. The idea of Paper 2 that consumers create a coalition in the market has also been considered among others by Menniti et al. (2006 and 2009). These formulations are receiving increasing interest today, see, e.g., Yammani and Prabhat (2018), Kou et al. (2020). Smart metering technologies allow the development of new strategies for collaborative coalitions where the coalition can also produce electricity. This results in multilevel coordination models, see, e.g., Brusco et al. (2014). Similarly the introduction of a demand response aggregator results in a three level setting which is approached by bi-level optimization by Feng et al. (2020). With these opportunities offered by digitalization technology and increase of sustainable consumption goals there is a growing interest in new kinds of business models in the energy communities including cooperative coalitions, for a review, see Reis et al. (2021).

2.5.2 Industrial energy management

There are different perspectives and levels to be considered in industrial optimization approaches. Problems are typically dynamic and have multiple objectives. There are many industrial settings in which there is a dynamic energy cost and a challenging production scheduling problem. For an illustrative summary, see Merkert et al. (2015). The paper describes different approaches to the production scheduling problem when the dynamic pricing of electricity is also considered. Gahm et al. (2016) provide an extensive survey on energy-efficient scheduling in manufacturing companies, which clearly shows the richness of the problems need to be considered in energy optimization. The solution methods are also different. Wang et al. (2018) consider job-shop scheduling and they apply a modified genetic algorithm at the first machine tool selection stage and a hybrid method that integrates genetic algorithm with particle swarm optimization at the second operation sequencing stage.

The combined optimization of production planning and energy use has for long been an important challenge in industry. The range of optimization approaches used is wide. Recently Leenders et al. (2022) studied the problem with a similar bi-level optimization approach as considered in Paper 5. The use of bi-level optimization is still relatively new and, e.g., Leenders et al. (2022) claim that their model would be the first one to use it. In their set up, the production planning system represents the upper level and the energy management system the lower level. The time dependent energy demand from the production planning system acts as a coupling constraint to the lower level energy scheduling problem. The problem is solved iteratively by gradually fixing the time depended states of the energy production units on the lower level. For an extensive recent survey about combining energy use with production planning, see Terbrack et al. (2021).

3. Research contribution

The overview of the dissertation is presented in Figure 7. The papers study methods and approaches to solve dynamic multiobjective and bi-level optimization problems arising from real life cases. The practical problems considered relate to environmental management and energy markets. One case is the management of a lake-river system over time and the others consider residential and industrial demand side management settings where the price of electricity varies over time. Methodologically dynamic multiobjective optimization is used in both problem areas in Papers 1-4. Bi-level optimization approaches are used in the electricity market cases in Papers 2 and 5. Paper 2 includes both of the methodological themes.

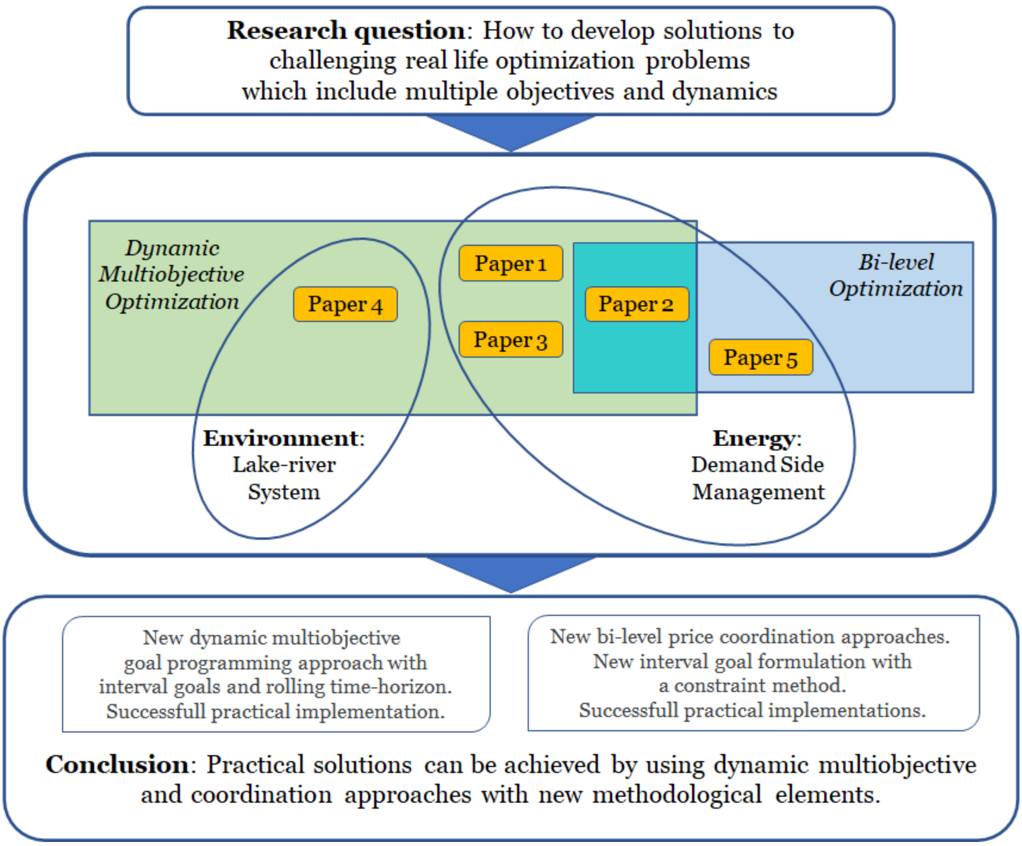


Figure 7. Overview of the dissertation.

The papers present new methodological developments as well as new ways of using traditional multiobjective optimization methods. They also provide new formulations to the practical problems. The summaries of the papers are presented in Table 1.

Table 1: Summary of the topics, objectives, approaches and results of the papers

Paper	Topic	Objective	Approach	Results
Paper 1	Smart reactive space heating home-owner customers in the electricity market.	To build a model for the estimation of the load of the electricity distributor when customers optimize their space heating strategies subject to the time varying price of electricity. To provide a tool for home-owners to optimize their thermal comfort and electricity cost.	A dynamic multiobjective space heating model for the house and thermal comfort of the consumer is developed. The model generates the load estimate for the distributor.	The implementation of the model in a spreadsheet program was successful and it provided a working tool.
Paper 2	A coalition of cooperative space heating customers in the electricity market.	To find an optimal time-of-use electricity tariff within the coalition which maximizes the overall utility of the customers. The utility of each customer type depends on the hourly deviations of thermal living comfort and total cost.	The space heating model of Paper 1 is used and an iterative price coordination approach is developed to find an optimal electricity tariff.	The price coordination approach was able to produce solutions in a computational example that included three consumer types.
Paper 3	Smart space heating of a home under time varying price of electricity.	To find an optimal heating strategy minimizing deviations from thermal comfort under time varying price of electricity.	The space heating model of Paper 1 was used. A dynamic goal programming model with interval goals is developed. The solution is generated by using a GPϵ constraint method.	The implementation of the model and the solution method in the spreadsheet program was successful. The capability of the GPϵ method to produce Pareto optimal solutions was theoretically proven.
Paper 4	Decision support for the regulation of a lake-river system.	To generate a forward looking regulation strategy which takes into account the lake dynamics and satisfies both soft and hard flow rate constraints in the river when inflow forecasts are updated only periodically.	A dynamic goal programming model with interval goals and a rolling planning horizon solution method are developed.	The model and the solution method were implemented successfully in a spreadsheet program. They were found to produce good strategies that were used in real life practice too.
Paper 5	Demand side management in industry by joint optimization of production planning and energy supply.	To develop an approach for the joint optimization of production planning and energy supply.	Optimization approaches based on decomposition are developed. The iterative price coordination approach is found to be applicable.	The price coordination approach and its computational procedure were successfully tested in two real-world cases. Convergence of the computational approach cannot be guaranteed in general.

3.1 Paper 1 - Dynamic multiobjective optimization model for space heating and load analysis

Paper 1 introduces an implementation of a demand side management model for a space heating consumer as a dynamic multiobjective optimization problem. As far as the author knows, it is among the first papers where the dynamic demand response of consumers is related to living comfort. Paper 1 also implements an agent based modeling framework for the electricity distributor to take the customers' responses into account when setting the electricity tariff. Paper 1 introduced the concept and the approach was further developed and analyzed in Papers 2 and 3.

In the model introduced in Paper 1, the dynamic multiobjective optimization problem is obtained when the decision maker, i.e., the home-owner, in an electrically heated house optimizes the hourly indoor temperature subject to the time varying price of electricity and outdoor temperature. The dynamics are also driven by the capability of the house to act as a heat storage. The objective function for living comfort is defined as a weighted sum of quadratic penalties of hourly deviations from the goal indoor temperatures over the day. The total heating costs over the day is another objective function. A weighted sum of these objective functions is used as a scalarizing function which leads into a standard linearly constrained quadratic optimization problem. The nonlinear optimization method included in the Excel spreadsheet program is utilized for solving the model. The prototype spreadsheet implementation of the model could be used with real house-owners since its user interface is simple.

The idea of including thermal comfort as an objective was a novel idea which has received an increasing interest only much later in the literature, see, e.g, Yang and Wang (2012). Today there is a wide interest in multiobjective formulations for comfort and more detailed objective functions have been suggested, see, e.g., Enescu (2017).

Paper 1 also demonstrated the power of spreadsheet programs as a prototyping environment for small sized optimization and decision making problems. The spreadsheet environment allows to integrate data and parameters handling, build an optimization model and solve it with the embedded nonlinear programming solver, and finally to illustrate the results graphically in a user friendly way. At the time of writing Paper 1, the use of spreadsheet programs as a framework for complicated optimization problems was still uncommon. The use of spreadsheet programs for modeling has continued and widened. Often the goal is to create a prototype, see, e.g, Briones et al. (2019). Naturally, there are practical limitations when the problem sizes grow but today even portable computers allow relatively large problems to be handled.

3.2 Paper 2 - Price coordination in deregulated electricity markets

Paper 2 considers a demand side management problem within the coalition of space heating consumers with different price reaction characteristics. It continues from the setting described in Paper 1 which included both dynamic price and dynamic multiobjective optimization. A new extension to the model is to consider a coalition of cooperative space heating consumers buying electricity with a single contract at a time varying price. The coalition aims at joint optimization of the cost of their total load by creating a joint time-of-use tariff within the coalition. In this two-level setting, the decision maker, i.e., the coalition coordinator, purchases the energy from the market and sets the time-of-use price to the consumers so that the overall social benefit is maximized.

This setting was a new contribution and an early paper on two-level market models. Recently, similar models have been considered in the literature. For example, see the paper by Yammani and Prabhat (2018) that presents a two-level formulation with an intermediary virtual operator. Today there is already interest in multiple level collaboration possibilities in energy markets, see, e.g., Guerrero et al. (2020) and Kou et al. (2020). Paper 2 was also an early introduction of agent based modeling to the literature on electricity markets. Agent based modeling of electricity markets has become already quite popular, see, e.g., Ringler et al. (2016).

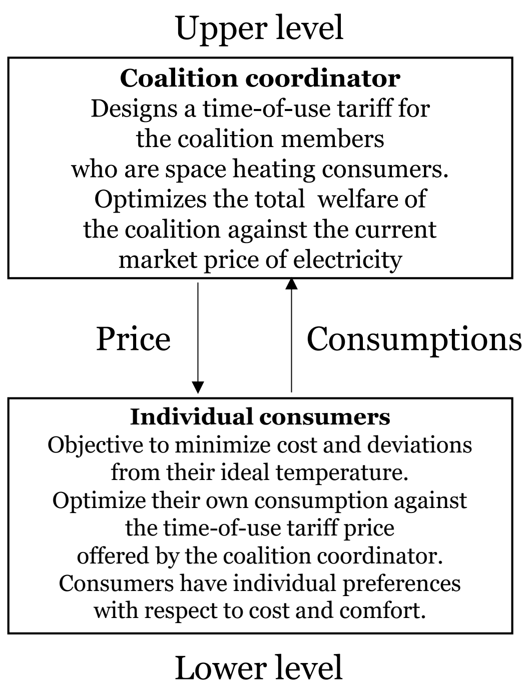


Figure 8. Price coordination in a coalition of electric space heaters.

The solution method developed in Paper 2 is an iterative approach based on price coordination. In the approach, price and consumption patterns are information signals exchanged between the coalition coordinator and the consumers as illustrated in Figure 8. In order to identify the coalition's optimal time-of-use tariff, the following steps are carried out. The consumption pattern for different consumer groups is gained from their own optimal reactions to the time varying tariff. Next, a new tariff is calculated by maximizing the total welfare of the coalition. In the last step, a closest tariff by minimizing the quadratic difference between the tariff and the marginal price is solved. This scheme was shown to converge in the example case with three consumer classes although, in general, the convergence is hard to guarantee.

It is also noteworthy that the space heating model presented in Paper 2 has been followed by a model for the optimal use of air conditioning (Menniti et a. 2009). A similar demand side management problem is also studied more recently in a paper by Ekaterina et al. (2019).

3.3 Paper 3 - Dynamic goal programming combined with a constraint method

Paper 3 further elaborates the multiobjective space heating problem of the decision maker, i.e., the home-owner, considered in Papers 1 and 2. The extended model introduced in Paper 3 uses a goal programming with interval goals for the indoor temperature at different times of the day. Some objectives are converted into constraints by defining upper bounds for these objectives as in the constraint method, and goals are used for other objectives. This results in a new dynamic multiobjective solution method that combines the traditional weighting, goal programming and constraint methods. The new method is called the GPϵ method. In the space heating problem, objectives related to the energy consumption and heating costs are constrained with upper bounds. These bounds are used together with living comfort relaxation which means that the indoor temperature is not constrained with a strict upper bound – instead the interval goal temperature is applied. The implementation of the model and the method was carried out using the Excel spreadsheet program.

Figure 9 illustrates the solutions generated by the weighting and GPϵ methods. When using a weighting method different weights are given for heating costs and living discomfort objectives. In the GPϵ method, each solution corresponds to a given constrained level of heating costs and goal preferences over living discomfort. The GPϵ method produces rather evenly distributed Pareto solutions. This is a desired property for multiobjective methods, see, e.g., a recent survey by Cui et al. (2017). The commonly used weighting method does not perform well in this respect for the house heating problem.

It is worth mentioning that the space heating model has been later used as a test model when new methods are developed, see Orouskhani et al. (2019) and Falahiazar et al. (2022).

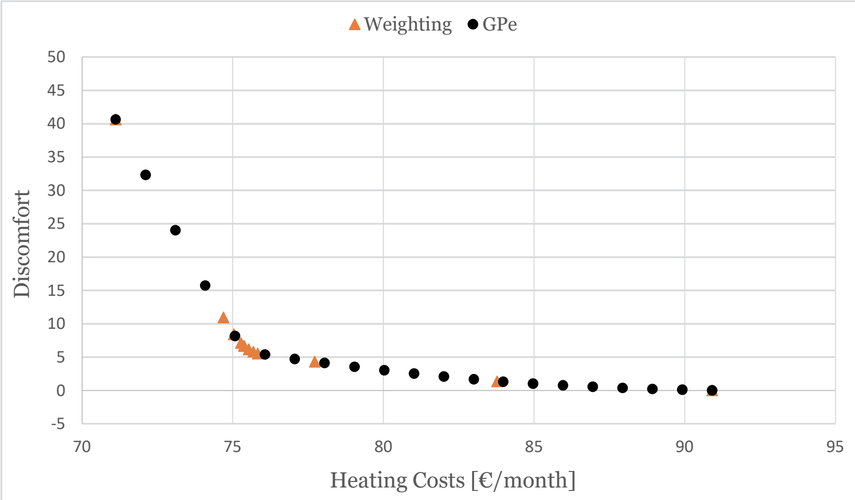


Figure 9. Pareto solutions in the objective space generated by the weighting and GPε methods for the house heating problem.

3.4 Paper 4 - Dynamic rolling horizon and interval goals in goal programming

Paper 4 develops a model to regulate a lake-river system consisting of a series of four lakes and a connecting river, see Figure 10. The overall goal is to find a regulation policy which keeps the water level of the lakes and the flow rate of the river within acceptable limits at different times of the year and under different weather conditions. These limits are specified by the general rules set by the authorities for the river system. Thus, the regulation rule for the flow rate in the river introduces strict lower and upper bounds for this rate and its changes. However, the flow rate bounds cannot always be met in practice and, therefore, they are represented as soft constraints using penalties in the lake-river system model. The water levels of the lakes are driven by the difference between the inflow and outflow of the main lake, and the levels also depend on the surface area of the main lake. The dependence between this area and lake's water level is approximated with a piecewise linear function using historical data.

The goal programming approach developed in Paper 4 was used to generate different regulation policy candidates. The evaluation of possible regulation policies was based on 30 primary and 27 secondary economical, social and natural objectives. The new solution approach uses both dynamic goal points and dynamic interval goal sets of water level. Here, quadratic penalty functions for the deviations from the water level goals were used as a distance measure. The use of interval goals for water reservoirs, that is for inflows and reservoir levels, was noted already early in Loganathan and Bhattacharya (1990), however in Paper 4 also an additional goal points within the goal intervals are used.

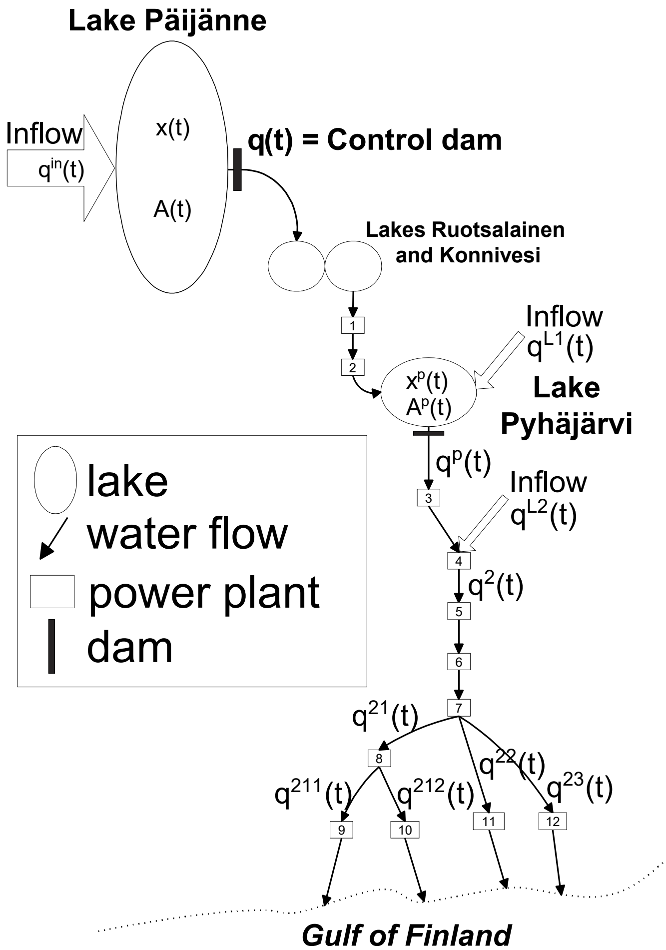


Figure 10. Description of the lake-river system of Päijänne-Kymijoki in Paper 4.

The lake-river model was planned to be used in the real life setting where the rate of incoming water is uncertain and it varies greatly both seasonally and annually. In practice, the inflow forecasts to the lake-river system are updated periodically and repetitive updating of the regulation policy is needed. To take this into account in the model, an innovative rolling horizon goal optimization approach was developed. It updates the solution with new look-ahead goal points. This approach describes the actual decision environment of the decision maker, i.e., the operational regulator.

The model and the solution approach were implemented with the Excel spreadsheet program. The implementation included handling of data, lake-river dynamics, visualizing of the results, and a user interface for operating the model and defining parameters related to water level goals. The implementation was successful, but the spreadsheet platform had its limitations. The size of the model made it hard to maintain, and computing the solutions was slow at the time of publication of Paper 4. Multiple computers were needed to obtain solutions with different parameter values. In fact, a whole computer classroom with tens of computers was reserved for days to produce the whole set of solutions which were of interest.

Later in the literature the lake-river model has been used as a reference case when evaluating a new solution approach. It was utilized in Orouskhani et al. (2019) when evaluating their evolutionary dynamic multiobjective Borda method.

3.5 Paper 5 - Price coordination in industrial production planning and energy optimization

Paper 5 introduces a coordination approach for industrial settings when combining production planning and energy supply optimization. The traditional sequential approach in the process industry has been that the production schedule is determined first. This is followed by energy supply optimization where the portfolio of energy purchases and generation is optimized, e.g., using a generalized minimum-cost flow network model presented in the appendix of Paper 5. The sequential approach does not, however, guarantee overall optimality. A new approach, illustrated in Figure 11, is developed using the idea of price coordination where the overall problem is solved iteratively using two separated optimization problems. The iterative coordination approach works such that the internal time varying price of the energy is updated in the energy optimization part for the given demand obtained from the production optimization part. Correspondingly, the production is optimized for the given price which results in a new demand for energy.

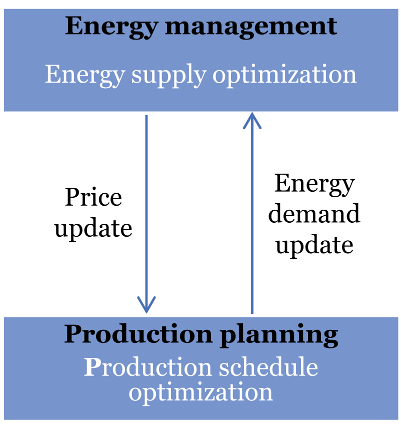


Figure 11. Coordination approach in combined production planning and energy supply optimization.

The coordination approach resulted from the analysis of the overall model combining production planning and energy supply optimization. The Bender's and Danzig-Wolfe's decomposition schemes were first applied to the overall model. The resulting master problem of the decomposition scheme was not tractable with either of these. A coordination approach based on the mean value cross decomposition algorithm of Holmberg (1992) was also studied. This algorithm iterates between the Lagrangian dual (Danzig-Wolfe) subproblem and Benders primal subproblem. The algorithm exchanges values of decision variables, in this case demand patterns, from the dual subproblem to the primal subproblem. The tested iterative updating schemes for both the price and demand patterns included three gradual and one heuristic schemes. The one-sided weighted mean value cross decomposition scheme (Holmberg 1999), updating only one of the patterns, namely price, in each iteration, was found to produce the best convergence towards the optimal solution.

The performance of the approach was tested in numerical examples in which real data from a thermo mechanical pulping process in the pulp and paper industry and a stainless-steel production process in the steel industry were used. The decision maker could be either the production planner or the energy manager of the mill site. The suggested coordination approach cannot be guaranteed to converge to the optimal solution in general, see Holmberg (1997), but in the numerical examples presented in Paper 5, it was able to produce near-optimal solutions. The coordination approach in Paper 5 could be extended to a multi mill production planning environment where energy supply takes place in centralized energy management centers. In this case price setting on the upper level would take into consideration the responses from different mills and possible sales and purchase agreements and generation units available for the centralized energy management.

4. Summary and future research directions

The contributions of this dissertation are two-fold. First, new approaches have been developed to model real life problems. Secondly, new methodological ideas have been presented to generate the solutions to these problems in practice.

Demand side management in the electricity market is one problem area. A new model was developed for space heating home-owners to optimize comfort and costs under the time varying price of electricity. The model for comfort was studied both with goal points and with goal intervals. Using this model, the electricity distributor could design the time-of-use tariff by taking into account the customer reactions. The coalition of cooperative consumers was a new setting and the bi-level problem was found to be solvable by a price coordination approach. The bi-level coordination setting in Paper 2 was an early contribution on two-level market models which have recently received strong interest.

The model developed for the regulation of a lake-river system reflected the practical operational requirements at the time and it included interval goals and a rolling planning horizon. The model was solved successfully with the methods developed. It was also accepted as a tool to support practical operational management.

The industrial problem of combined production planning and energy supply optimization was formulated as a bi-level optimization problem. A successful solution was found by the price coordination algorithm developed.

The theoretical contributions of the dissertation are related to the development of new multiobjective optimization methods. One of them was the use of interval goals in dynamic goal programming which was new at the time. The GP$\in$ method developed in connection with the space heating problem was also a new contribution. The price coordination approaches in Papers 2 and 5 for the bi-level optimization problems proved to be useful.

There are different future research directions in the settings considered in the dissertation. The popularity of the Excel spreadsheet program discussed in Papers 1, 3 and 4 has continued over the years. A recent application example is given by Pačaiová et al. (2021). They use Excel for prototyping and optimization. To tackle more complicated practical problems, one still needs to consider other frameworks. In recent years, there has been progress in modeling frameworks, such as GAMS or LPL[1]. In addition, Python and Julia programming languages and their modeling libraries, such as Pyomo, Pymoo and JuMP[2], have increased their popularity in applications. According to my personal experience, the use of spreadsheet programs as the first line of prototyping platforms in optimization studies has continued within the process industry.

The optimal responses of coalitions of consumers in the electricity market discussed in Paper 2 is a theme which is quite relevant today as new technologies provide possibilities for realistic applications of the new approaches. The two-level setting continues to draw interest, see, e.g., Soares et al. (2020) and Zhao et al. (2021). The topic is likely to receive increasing interest in particular in the literature on smart grids and in combined district energy systems (Capone et al. 2021). The agent based approach (see Weidlich et al. 2008, Ringler et al. 2016) and the demand side response mechanisms (see, e.g., Menniti et al. 2009, Sharifi et al. 2019) have continued to be of interest. Modeling comfort as a consumer's objective has also been further extended, see, e.g., Alves et al. (2018). It is interesting to note that the idea of price responsive house heating has already lead into commercial products[3]. The effect of the installation of home energy management systems studied by Tuomela et al. (2021) results in shifted consumption towards off-peak hours and reduction of total energy usage similarly as in Paper 2.

Interest in dynamic multiobjective optimization is clearly growing. The need for testing and evaluating dynamic multiobjective optimization methods in real-world applications have recently been emphasized by Helbig and Engelbrecht (2014) and Helbig et al. (2016). The dynamic interval goal programming approach considered in Papers 3 and 4 has not received much interest as of yet but it is also a theme which can be of more interest soon due to the needs to create more flexible approaches in smart grids based on wind and solar energy, see, e.g., Jones and Romero (2019). Evolutionary algorithms have received a growing interest as a possible solution approach (see, e.g., a survey in Azzouz et al. 2017). However, these algorithms face problems already in medium and, in particular, in large scale problems if getting one evaluation of objective functions is time consuming. This can be an issue when evaluation is based on solving other optimization problems like in the lake-river regulation. Thus, generating a population of multiple solutions can become practically intractable. A possible new research direction could be to utilize approximate dynamic programming methods (Powell 2011) used widely for single objective dynamic optimization to solve dynamic multiobjective problems.

The price coordination approaches developed in Papers 2 and 5 proved successful in producing solutions for bi-level optimization problems. The practical implementation does still require more investigation to assure the convergence and near optimality of solutions obtained. The combined production planning and energy management optimization has recently

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[1] GAMS: https://www.gams.com/ , LPL: https://virtual-optima.com/

[2] Pyomo: http://www.pyomo.org/ , Pymoo: https://pymoo.org/, JuMP: https://jump.dev/

[3] FORTUM: https://www.fortum.fi/kotiasiakkaille/sahkoa-kotiin/fiksu, OptiWatti: https://www.optiwatti.fi

received more attention, see, e.g., Terbrack et al. (2021). This could be one area of industrial applications where price coordination schemes might be of use. My personal opinion based on decades long experience in developing industrial solutions is that there is still a lot to be done in combining production planning and energy management optimization systems.

Applying multiobjective methods in practice requires the interaction of the modeler and the problem owners and stakeholders. This brings in the need to also consider behavioral factors in the whole problem solving process. Recent emergence of the new area of behavioral operational research (Hämäläinen et al. 2013) has raised important new research topics. These behavioral considerations are particularly important in environmental modeling (Hämäläinen 2015) where multiobjective models are commonly used. Today, there is also increased interest in behavioral studies analyzing and modeling the use of electricity to reach environmental targets, see, e.g., Lopes et al. (2020). This area is closely related to the models studied in Papers 1-3. An industrially interesting area would be behavioral obstacles and their overcoming related to the execution of industrial energy efficiency programs. So, this is clearly one direction of research in the future when applying multiobjective approaches.

In practical industrial settings, multiple optimization levels may exist, such as in planning with strategic, tactical and short-term horizons. In general, difficulties to find numerical solutions may easily arrive as the planning horizon grows. One might also be faced with model instances that are hard to solve even with modern solvers, such as CPLEX or Gurobi[4], see, e.g., Karjalainen et al. (2015). In today's demanding online world, problem's parameters may change rapidly and the time available for generating solutions can be restricted. Therefore, in practice, there can be interest in generating satisfying near optimal solutions using different heuristics like rolling time horizon window or price coordination approaches elaborated in this dissertation. For these solutions, fast heuristic methods can possibly be found (Grossmann 2012). The integration of energy costs and the environmental impacts of energy production into industrial production planning especially in multiple planning levels is an area of future research which has, so far, been overlooked.

As a practice-oriented conclusion, one can expect to see an increasing number of real-world applications using the modern methods of dynamic multiobjective and bi-level optimization. Potential application areas are versatile ranging from environmental and energy problems to industrial enterprise-wide planning tasks.

[4] CPLEX: https://www.ibm.com/analytics/cplex-optimizer, Gurobi: https://www.gurobi.com

References

Acuña, L. G., Ríos, D. R., Arboleda, C. P., and Ponzón, E. G. (2018). Cooperation model in the electricity energy market using bi-level optimization and Shapley value. Operations Research Perspectives, 5, 161–168. doi: 10.1016/j.orp.2018.07.003.

Aghaei Pour, P., Rodemann, T., Hakanen, J., and Miettinen, K. (2021). Surrogate assisted interactive multiobjective optimization in energy system design of buildings. Optimization and Engineering, 2021, Published online: 05 January 2021. doi: 10.1007/s11081-020-09587-8.

Álvarez, J. D., Redondo, J. L., Camponogara, E., Normey-Rico, J., Berenguel, M., and Ortigosa, P. M. (2013). Optimizing building comfort temperature regulation via model predictive control. Energy and Buildings, 57, 361-372. doi: 10.1016/j.enbuild.2012.10.044.

Alves, M. J., Antunes, C. H., and Carrasqueira, P. (2016). A hybrid genetic algorithm for the interaction of electricity retailers with demand response. In proceedings: Squillero, G., Burelli, P. (Eds.), Applications of Evolutionary Computation. EvoApplications 2016, Porto, Portugal, 30 March – 1 April, 2016. Lecture Notes in Computer Science, vol. 9597, 459–474. Springer, Cham. doi: 10.1007/978-3-319-31204-0_30.

Alves, M. J., and Antunes, C. H. (2018). A semivectorial bilevel programming approach to optimize electricity dynamic time-of-use retail pricing. Computers & Operations Research, 92, 130–144. doi: 10.1016/j.cor.2017.12.014.

Antunes, C. H., Alves, M. J., and Climaco, J. (2016). Multiobjective Linear and Integer Programming. EURO Advanced Tutorials on Operational Research, 1st ed. Springer, Cham. doi: 10.1007/978-3-319-28746-1.

Antunes, C. H., Alves, M. J., and Ecer, B. (2020). Bilevel optimization to deal with demand response in power grids: models, methods and challenges. Top, 28(3), 814-842. doi: 10.1007/s11750-020-00573-y.

Asadi, E., da Silva, M. G., Antunes, C. H., and Dias, L. (2012). Multi-objective optimization for building retrofit strategies: A model and an application. Energy and Buildings, 44, 81–87. doi: 10.1016/j.enbuild.2011.10.01610.1016.

Ascione, F., Bianco, N., De Stasio, C., Mauro, G. M., and Vanoli, G. P. (2016). Simulation-based model predictive control by the multi-objective optimization of building energy performance and thermal comfort. Energy and Buildings, 111, 131-144. doi: 10.1016/j.enbuild.2015.11.033.

Ascione, F., Bianco, N., De Masi, R. F., Mauro, G. M., and Vanoli, G. P. (2017). Energy retrofit of educational buildings: Transient energy simulations, model calibration and multi-objective optimization towards nearly zero-energy performance. Energy and Buildings, 144, 303–319. doi: 10.1016/j.enbuild.2017.03.056.

Ascione, F., Bianco, N., Mauro, G. M., Napolitano, D. F., and Vanoli, G. P. (2019). Weather-data-based control of space heating operation via multi-objective optimization: Application to Italian residential buildings. Applied Thermal Engineering, 163, 114384. doi: 10.1016/j.applthermaleng.2019.114384.

Azzouz, R., Bechikh, S., and Said, L. B. (2017). Dynamic multi-objective optimization using evolutionary algorithms: a survey. In: Bechikh S., Datta R., Gupta A. (eds), Recent Advances in Evolutionary Multi-objective Optimization. Adaptation, Learning, and Optimization, vol. 20, 31–70. Springer, Cham. doi: 10.1007/978-3-319-42978-6_2.

Ben-Ayed, O., and Blair, C. E. (1990). Computational difficulties of bilevel linear programming. Operations Research, 38(3), 556–560. doi: 10.1287/opre.38.3.556.

Bracken, J., and McGill, J. T. (1973). Mathematical programs with optimization problems in the constraints. Operations Research, 21(1), 37–44. doi: 10.1287/opre.21.1.37.

Benders, J. F. (1962). Partitioning procedures for solving mixed-variables programming problems. Numerische Mathematik 4(1), 238–252. doi.org: 10.1007/BF01386316.

Briones, L., and Escola, J. M. (2019). Application of the microsoft excel solver tool in the solution of optimization problems of heat exchanger network systems. Education for Chemical Engineers, 26, 41–47, 2019. doi: 10.1016/j.ece.2018.10.003.

Brusco, G., Burgio, A., Menniti, D., Pinnarelli, A., and Sorrentino, N. (2014). Energy management system for an energy district with demand response availability. IEEE Transactions on Smart Grid 5(5), 2385–2393. doi: 10.1109/TSG.2014.2318894.

Can, E. K., and Houck, M. H. (1984). Real-time reservoir operations by goal programming. Journal of Water Resources Planning and Management 110(3), 297–309. doi: 10.1061/(ASCE)0733-9496(1984)110:3(297).

Capone, M., Guelpa, E., and Verda, V. (2021). Multi-objective optimization of district energy systems with demand response. Energy 227, 120472. doi: 10.1016/j.energy.2021.120472.

Charnes, A., Cooper, W., and Ferguson, R. (1955). Optimal estimation of executive compensation by linear programming. Management Science, 1(2), 138–151. Stable link: http://www.jstor.org/stable/2627315.

Chegari, B., Tabaa, M., Simeu, E., Moutaouakkil, F., and Medromi, H. (2021). Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms. Energy and Buildings, 239, 110839. doi: 10.1016/j.enbuild.2021.110839.

Colapinto, C., Jayaraman, R., and Marsiglio, S. (2017). Multi-criteria decision analysis with goal programming in engineering, management and social sciences: a state-of-the art review. Annals of Operations Research, 251(1), 7–40. doi: 10.1007/s10479-015-1829-1.

Cui, Y., Geng, Z., Zhu, Q., and Han, Y. (2017). Review: Multi-objective optimization methods and application in energy saving. Energy, 125, 681–704. doi: 10.1016/j.energy.2017.02.174.

Dantzig, G. B., and Wolfe, P. (1960). Decomposition principle for linear programs. Operations Research 8(1), 101–111. doi: 10.1287/opre.8.1.101.

D'Cruz, N. A., and Radford, A. D. (1987). A multicriteria model for building performance and design. Building and Environment, 22(3), 167–179. doi: 10.1016/0360-1323(87)90005-9.

Deb, K. (2001). Multi-Objective Optimization Using Evolutionary Algorithms, Wiley-Interscience series in systems and optimization. John Wiley & Sons, Hoboken, England, 2001.

Deb, K., and Jain, H. (2014). An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, Part I: Solving Problems With Box Constraints. IEEE Transactions on Evolutionary Computation, 18(4), 577–601. doi: 10.1109/TEVC.2013.2281535.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182–197. doi: 10.1109/4235.996017.

Deb, K., Rao N., U. B., and Karthik, S. (2007). Dynamic multi-objective optimization and decision-making using modified NSGA-II: a case study on hydro-thermal power scheduling. In proceedings: Obayashi, S., Deb, K., Poloni, C., Hiroyasu, T., Murata, T. (Eds.), Evolutionary Multi-Criterion Optimization. EMO 2007, Matsushima, Japan, 5–8 March, 2007. Lecture Notes in Computer Science, vol. 4403, 803–817. Springer Berlin Heidelberg, Berlin, Heidelberg. doi: 10.1007/978-3-540-70928-2_60.

Dempe, S., Kalashnikov, V., Pérez-Valdés, G. A., and Kalashnykova, N. (2015). Bilevel Programming Problems - Theory, Algorithms and Applications to Energy Networks. Energy Systems. Springer, Berlin, Heidelberg, 2015. doi: 10.1007/978-3-662-45827-3.

Dempe, S. (2020). Bilevel Optimization: Theory, Algorithms, Applications and a Bibliography, in book: Dempe, S., and Zemkoho, A. (eds.), Bilevel Optimization: Advances and Next Challenges, 581–672. Springer International Publishing, Cham. doi: 10.1007/978-3-030-52119-6_20.

Duckstein, L., and Opricovic, S. (1980). Multiobjective optimization in river basin development. Water Resources Research, 16(1), 14–20. doi: 10.1029/WR016i001p00014.

Ekaterina, A., Luce, B., Sébastien, L., and Alain, M. (2019). A bilevel approach to optimize electricity prices. Yugoslav Journal of Operations Research, 29(1), 9–30. doi: 10.2298/YJOR171115002A.

Enescu, D. (2017). A review of thermal comfort models and indicators for indoor environments. Renewable and Sustainable Energy Reviews, 79, 1353–1379. doi: 10.1016/j.rser.2017.05.175.

Eschenbach, E. A., Magee, T., Zagona, E., Goranflo, M., and Shane, R. (2001). Goal programming decision support system for multiobjective operation of reservoir systems. Journal of Water Resources Planning and Management, 127(2), 108-120. doi: 10.1061/(ASCE)0733-9496(2001)127:2(108).

Falahiazar, A., Sharifi, A., and Seydi, V. (2022). An efficient spread-based evolutionary algorithm for solving dynamic multi-objective optimization problems. Journal of Combinatorial Optimization, 44(1), 794-849. doi: 10.1007/s10878-022-00860-3.

Farina, M., Deb, K., and Amato, P. (2004). Dynamic multiobjective optimization problems: test cases, approximations, and applications. IEEE Transactions on Evolutionary Computation, 8(5), 425–442. doi: 10.1109/TEVC.2004.831456.

Feng, C., Li, Z., Shahidehpour, M., Wen, F., and Li, Q. (2020). Stackelberg game based transactive pricing for optimal demand response in power distribution systems. International Journal of Electrical Power & Energy Systems, 118, 105764. doi: 10.1016/j.ijepes.2019.105764.

Gass, S., and Saaty, T. (1955). The computational algorithm for the parametric objective function. Naval Research Logistics Quarterly, 2(1-2), 39–45. doi: 10.1002/nav.3800020106.

Gassar, A. A. A., Koo, C., Kim, T. W., and Cha, S. H. (2021). Performance optimization studies on heating, cooling and lighting energy systems of buildings during the design stage: A review. Sustainability, 13(17), 9815. doi: 10.3390/su13179815.

Chankong, V., and Haimes, Y. Y. (1983). Multiobjective decision making: theory and methodology. North-Holland, New York, 1983.

Gero, J. S., D'Cruz, N., and Radford, A. D. (1983). Energy in context: A multicriteria model for building design. Building and Environment, 18(3), 99–107. doi: 10.1016/0360-1323(83)90001-X.

Gahm, C., Denz, F., Dirr, M., and Tuma, A. (2016). Energy-efficient scheduling in manufacturing companies: A review and research framework. European Journal of Operational Research, 248(3), 744-757. doi: 10.1016/j.ejor.2015.07.017.

Gomes, A., Antunes, C. H., and Martins, A. G. (2007). A multiple objective approach to direct load control using an interactive evolutionary algorithm. IEEE Transactions on Power Systems, 22(3), 1004–1011. doi: 10.1109/TPWRS.2007.901468.

Grossmann, I. E. (2012). Advances in mathematical programming models for enterprise-wide optimization. Computers and Chemical Engineering, 47, 2–18. doi: 10.1016/j.compchemeng.2012.06.038.

Haimes, Y. Y., and Hall, W. A. (1974). Multiobjectives in water resource systems analysis: The Surrogate Worth Trade Off Method. Water Resources Research, 10(4), 615–624. doi: 10.1029/WR010i004p00615.

Hamdy, M. (2012). Combining Simulation and Optimisation for Dimensioning Optimal Building Envelopes and HVAC Systems (Doctoral thesis). Aalto University publication series DOCTORAL DISSERTATIONS; 177/2012. School of Engineering. http://urn.fi/URN:ISBN:978-952-60-4938-0.

Helbig, M., and Engelbrecht, A. P. (2014). Population-based metaheuristics for continuous boundary-constrained dynamic multi-objective optimisation problems. Swarm and Evolutionary Computation, 14, 31–47. doi: 10.1016/j.swevo.2013.08.004.

Helbig, M., Deb, K., and Engelbrecht, A. (2016). Key challenges and future directions of dynamic multi-objective optimisation. In proceedings: 2016 IEEE Congress on Evolutionary Computation (CEC), Vancouver, BC, Canada, 2016. 1256–1261. doi: 10.1109/CEC.2016.7743931.

Hirvonen, J. (2017). Towards zero energy communities: Increasing local and renewable energy utilization in buildings through shared energy generation and storage (Doctoral thesis). Aalto University publication series DOCTORAL DISSERTATIONS; 99/2017. School of Engineering. http://urn.fi/URN:ISBN:978-952-60-7451-1.

Hojjati, A., Monadi, M., Faridhosseini, A., and Mohammadi, M. (2018). Application and comparison of NSGA-II and MOPSO in multi-objective optimization of water resources systems. Journal of Hydrology and Hydromechanics, 66(3), 323-329. doi: 10.2478/johh-2018-0006.

Holmberg, K. (1992). Linear mean value cross decomposition: A generalization of the Kornai-Liptak method. European Journal of Operational Research, 62(1), 55–73. doi: 10.1016/0377-2217(92)90177-B.

Holmberg, K. (1994). A convergence proof for linear mean value cross decomposition. Zeitschrift für Operations Research, 39(2), 157–186. doi: 10.1007/BF01415580.

Holmberg, K. (1997). Mean value cross decomposition applied to integer programming problems. European Journal of Operational Research, 97(1), 124–138. doi: 10.1016/S0377-2217(96)00139-7.

Holmberg, K. (1999). Mean value cross decomposition based branch-and-bound for mixed integer programming problems. In proceedings: Kall P., Lüthi HJ. (eds), Operations Research Proceedings 1998. Selected Papers of the International Conference on Operations Research Zurich, 31 August – 3 September, 1998. vol. 1998, 200-209. Springer, Berlin, Heidelberg. doi: 10.1007/978-3-642-58409-1_20.

Hämäläinen, R. P. (2015). Behavioural issues in environmental modelling – the missing perspective. Environmental Modelling & Software, 73, 244–253. doi: 10.1016/j.envsoft.2015.08.019.

Hämäläinen, R. P., Luoma, J., and Saarinen, E. (2013). On the importance of behavioral operational research: The case of understanding and communicating about dynamic systems. European Journal of Operational Research, 228(3), 623–634. doi: 10.1016/j.ejor.2013.02.001.

Jiang, S., Zou, J., Yang, S., and Yao, X. (2022). Evolutionary dynamic multi-objective optimisation: A survey. Association for Computing Machinery (ACM), ACM Computing Surveys, 55(4). doi: 10.1145/3524495.

Jones, D., and Romero, C. (2019). Advances and new orientations in goal programming. In: Doumpos M., Figueira J., Greco S., Zopounidis C. (eds), New Perspectives in Multiple Criteria Decision Making. Multiple Criteria Decision Making, 231–246. Springer, Cham. doi: 10.1007/978-3-030-11482-4_8.

Jones, D., and Tamiz, M. (2010). Practical goal programming. International Series in Operations Research and Management Science, Springer, Boston, MA, edition 1. doi: 10.1007/978-1-4419-5771-9.

Jridi, I., Jerbi, B., and Kamoun, H. (2018). Menu planning with a dynamic goal programming approach. Multiple Criteria Decision Making, 13, 74–87. dx.doi: 10.22367/mcdm.2018.13.04.

Karjalainen, J., Kymäläinen, T., Mäntysaari, J., and Kauppala, T. (2015). Optimizing energy flows. ABB Review, 4, 15, 68–72. Stable link: https://library.e.abb.com/public/d7fd367687a449b1be893a6a4d1133c8/ABB%20Review%204-2015_72dpi.pdf

Kirimtat, A., Krejcar, O., Kertesz, A., and Tasgetiren, M. F. (2020). Future trends and current state of smart city concepts: a survey. IEEE Access, 8, 86448–86467. doi: 10.1109/ACCESS.2020.2992441.

Kuo, R. J., Lee, Y. H., Zulvia, F. E., and Tien, F. C. (2015). Solving bi-level linear programming problem through hybrid of immune genetic algorithm and particle swarm optimization algorithm. Applied Mathematics and Computation, 266, 1013–1026. doi: 10.1016/j.amc.2015.06.025.

Kou, X., Li., F., Dong, J., Starke, M., Munk, J., Xue, Y., Olama, M., and Zandi, H. (2020). A scalable and distributed algorithm for managing residential demand response programs using alternating direction method of multipliers (ADMM). IEEE Transactions on Smart Grid, 11(6), 4871–4882. doi: 10.1109/TSG.2020.2995923.

Labbé, M., and Violin, A. (2016). Bilevel programming and price setting problems. Annals of Operations Research, 240(1), 141–169. doi: 10.1007/s10479-015-2016-0.

Lachhwani, K., and Dwivedi, A. (2018). Bi-level and multi-level programming problems: taxonomy of literature review and research issues. Archives of Computational Methods in Engineering, 25(4), 847–877. doi: 10.1007/s11831-017-9216-5.

Leenders, L., Hagedorn, D.F., Djelassi, H., Bardow, A., and Mitsos, A. (2022). Bilevel optimization for joint scheduling of production and energy systems. Optimization and Engineering.doi: 10.1007/s11081-021-09694-0.

Li, B., Li, J., Tang, K., and Yao, X. (2015). Many-objective evolutionary algorithms: A survey. ACM Computing Surveys, 48(1), 1-35. doi: 10.1145/2792984.

Loganathan G. V., and Bhattacharya D. (1990). Goal-programming techniques for optimal reservoir operations. Journal of Water Resources Planning and Management 116(6), 820–838. doi: 10.1061/(ASCE)0733-9496(1990)116:6(820).

Lopes, M., Antunes, C. H., and Janda, K. B. (2020). Energy and behaviour: Challenges of a low-carbon future. In Energy and Behaviour (pp. 1-15, 153-175). Academic Press. doi: 10.1016/B978-0-12-818567-4.00030-2.

Mahmoud, M. S. (1977). Multilevel systems control and applications: a survey. IEEE Transactions on Systems, Man, and Cybernetics, 7(3), 125–143. doi: 10.1109/TSMC.1977.4309677.

Marttunen, M., Mustajoki, J., Dufva, M., and Karjalainen, T. P. (2015). How to design and realize participation of stakeholders in MCDA processes? A framework for selecting an appropriate approach. EURO Journal on Decision Processes, 3(1), 187–214. doi: 10.1007/s40070-013-0016-3.

Menniti, D., Sorrentino, N., Scordino, N., and Costanzo, F. (2006). Coalition of consumers in a deregulated electricity market: Analyses of consumption dynamics of air conditioning users. In: 2006 IEEE PES Power Systems Conference and Exposition, 1174-1181, IEEE. doi: 10.1109/PSCE.2006.296474

Menniti, D., Costanzo, F., Scordino, N., and Sorrentino, N. (2009). Purchase-bidding strategies of an energy coalition with demand-response capabilities. IEEE Transactions on Power Systems, 24(3), 1241–1255. doi: 10.1109/TPWRS.2009.2023750.

Merkert, L., Harjunkoski, I., Isaksson, A., Säynevirta, S., Saarela, A., and Sand, G. (2015). Scheduling and energy – industrial challenges and opportunities. Computers and Chemical Engineering, 72, 183–198. doi: 10.1016/j.compchemeng.2014.05.024.

Miettinen, K. (1999). Nonlinear multiobjective optimization. Kluwer Academic Publishers, Springer, Boston, MA, 1999. doi: 10.1007/978-1-4615-5563-6.

Miettinen, K., Hakanen, J., and Podkopaev, D. (2016). Interactive nonlinear multiobjective optimization methods. In: Greco, S., Ehrgott, M., Figueira, J.R. (Eds.), Multiple Criteria Decision Analysis: State of the Art Surveys. International Series in Operations Research & Management Science, vol 233, 927–976. Springer New York, New York, NY. doi: 10.1007/978-1-4939-3094-4_22.

Miettinen, K., and Mäkelä, M. M. (2002). On scalarizing functions in multiobjective optimization. OR Spectrum, 24(2), 193–213. doi: 10.1007/s00291-001-0092-9.

Mofidi, F., and Akbari, H. (2020). Intelligent buildings: An overview. Energy and Buildings, 223, 110192. doi: 10.1016/j.enbuild.2020.110192.

Nowak, M., and Trzaskalik, T. (2021). A trade-off multiobjective dynamic programming procedure and its application to project portfolio selection. Annals of Operations Research, 2021, Published online: 05 January 2021. doi: 10.1007/s10479-020-03907-y.

Oliveira, C., and Antunes, C. H. (2007). Multiple objective linear programming models with interval coefficients – an illustrated overview. European Journal of Operational Research, 181(3), 1434–1463. doi: 10.1016/j.ejor.2005.12.042.

Orouskhani, M., Teshnehlab M., and Nekoui, M. A. (2019). Evolutionary dynamic multi-objective optimization algorithm based on borda count method. International Journal of Machine Learning and Cybernetics, 10(8), 1931–59. doi: 10.1007/s13042-017-0695-3.

Pačaiová, H., Korba, P., Hovanec, M., Galanda, J., Šváb, P., and Lukáč, J. (2021). Use of simulation tools for optimization of the time duration of winter maintenance activities at airports. Sustainability, 13(3), 1095. doi: 10.3390/su13031095.

Pallante, A., Adacher, L., Botticelli, M., Pizzuti, S., Comodi, G., and Monteriu, A. (2020). Decision support methodologies and day-ahead optimization for smart building energy management in a dynamic pricing scenario. Energy and Buildings, 216, 109963. doi: 10.1016/j.enbuild.2020.109963.

Pineda, S., and Morales, J. M. (2019). Solving Linear Bilevel Problems Using Big-Ms: Not all that glitters is gold. IEEE Transactions on Power Systems, 34(3), 2469–2471. doi: 10.1109/TPWRS.2019.2892607.

Powell, W.B. (2011). Approximate Dynamic Programming: Solving the Curses of Dimensionality, 2nd Edition. ed, Wiley Series in Probability and Statistics. Wiley. http://dx.doi.org/10.1002/9781118029176.

Raquel, C., and Yao, X. (2013). Dynamic multi-objective optimization: a survey of the state-of-the-art. In: Yang, S., Yao, X. (Eds.), Evolutionary Computation for Dynamic Optimization Problems. Studies in Computational Intelligence, vol. 490, 85-106. Springer Berlin Heidelberg, Berlin, Heidelberg. doi: 10.1007/978-3-642-38416-5_4.

Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., and Kollat, J.B. (2013). Evolutionary multiobjective optimization in water resources: The past, present, and future. Advances in Water Resources, 51, 438–456. doi: 10.1016/j.advwatres.2012.01.005.

F. G. Reis, I., Gonçalves, I., A. R. Lopes, M., and Antunes, C. H. (2021). Business models for energy communities: A review of key issues and trends. Renewable and Sustainable Energy Reviews, 144, 111013. doi: 10.1016/j.rser.2021.111013.

Ringler, P., Keles, D., and Fichtner, W. (2016). Agent-based modelling and simulation of smart electricity grids and markets – A literature review. Renewable and Sustainable Energy Reviews, 57, 205-215. doi: 10.1016/j.rser.2015.12.169.

Said, R., Elarbi, M., Bechikh, S., and Ben Said, L. (2021). Solving combinatorial bi-level optimization problems using multiple populations and migration schemes. Operational Research. doi.org: 10.1007/s12351-020-00616-z.

Sharifi, R., Anvari-Moghaddam, A., Hamid Fathi, S. H., Guerrero, J. M., and Vahidinasab, V. (2019). An optimal market-oriented demand response model for price-responsive residential consumers. Energy Efficiency, 12(3), 803–815. doi: 10.1007/s12053-018-9713-x.

Siano, P. (2014). Demand response and smart grids - a survey. Renewable and Sustainable Energy Reviews, 30, 461–478. doi: 10.1016/j.rser.2013.10.022.

Sindhya, K., Ojalehto, V., Savolainen, J., Niemistö, H., Hakanen, J., and Miettinen, K. (2014). Coupling dynamic simulation and interactive multiobjective optimization for complex problems: an APROS-NIMBUS case study. Expert Systems with Applications, 41(5), 2546–2558. doi: 10.1016/j.eswa.2013.10.002.

Sinha, A., Malo, P., and Deb, K. (2018). A review on bilevel optimization: from classical to evolutionary approaches and applications. IEEE Transactions on Evolutionary Computation, 22(2), 276–295. doi: 10.1109/TEVC.2017.2712906.

Soares, I., Alves, M. J., and Antunes, C. H. (2020). Designing time-of-use tariffs in electricity retail markets using a bi-level model – estimating bounds when the lower level problem cannot be exactly solved. Omega, 93, 102027. doi: 10.1016/j.omega.2019.01.005d.

Stretch, D., and Adeyemo, J. (2018). Review of hybrid evolutionary algorithms for optimizing a reservoir. South african journal of chemical engineering, 25(1), 22-31. doi: 10.1016/j.sajce.2017.11.004.

Steuer, R.E., and Choo, E.U. (1983). An interactive weighted Tchebycheff procedure for multiple objective programming. Mathematical Programming 26(3), 326–344. doi: 10.1007/BF02591870.

Talbi, E.-G. (2013). A Taxonomy of Metaheuristics for Bi-level Optimization, in: Talbi, E.-G. (Ed.), Metaheuristics for Bi-Level Optimization. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 1–39. doi: 10.1007/978-3-642-37838-6_1.

Tang, K.S., Chan, T.M., Yin, R.J., and Man, K.F. (2012). Multiobjective optimization methodology: a jumping gene approach (1st ed.). CRC Press, 2012. doi: 10.1201/9781315216638.

Terbrack, H., Claus, T., and Herrmann, F. (2021). Energy-oriented production planning in industry: A systematic literature review and classification scheme. Sustainability 13(23), 13317. doi: 10.3390/su132313317.

Tohidi, Y., Farrokhseresht, M., and Gibescu, M. (2018). A review on coordination schemes between local and central electricity markets. In proceedings: 2018 15th International Conference on the European Energy Market (EEM), Lodz, Poland, 27-29 June, 2018. 1–5. doi: 10.1109/EEM.2018.8470004.

Tuomela, S., de Castro Tomé, M., Iivari, N., and Svento, R. (2021). Impacts of home energy management systems on electricity consumption. Applied Energy 299, 117310. doi: 10.1016/j.apenergy.2021.117310.

van Hoesel, S. (2008). An overview of Stackelberg pricing in networks. European Journal of Operational Research, 189(3), 1393–1402. doi: 10.1016/j.ejor.2006.08.064.

Van Roy, T. J. (1983). Cross decomposition for mixed integer programming. Mathematical Programming 25(1), 46–63. doi: 10.1007/BF02591718.

Vassoney, E, Mochet, A. M., and Comoglio, C. (2017). Use of multicriteria analysis (MCA) for sustainable hydropower planning and management. Journal of Environmental Management, 196, 48–55. doi: 10.1016/j.jenvman.2017.02.067.

Vesikar, Y., Deb, K., and Blank, J. (2018). Reference Point Based NSGA-III for Preferred Solutions. In proceedings: 2018 IEEE Symposium Series on Computational Intelligence (SSCI), Bengaluru, India, 18-21 November, 2018. 1587–1594. doi: 10.1109/SSCI.2018.8628819.

Virtanen, K., Raivio, T., Hämäläinen, R. P. (2004). Modeling pilot's sequential maneuvering decisions by a multistage influence diagram. Journal of Guidance, Control, and Dynamics 27(4), 665–677. doi.org: 10.2514/1.11167.

Wang, H., Jiang, Z., Wang, Y., Zhang, H., and Wang, Y. (2018). A two-stage optimization method for energy-saving flexible job-shop scheduling based on energy dynamic characterization. Journal of Cleaner Production, 188, 575-588. doi: 10.1016/j.jclepro.2018.03.254.

Weidlich, A., and Veit, D. (2008). A critical survey of agent-based wholesale electricity market models. Energy Economics, 30(4), 1728–1759. doi: 10.1016/j.eneco.2008.01.003.

Wierzbicki, A. P. (1982). A mathematical basis for satisficing decision making. Mathematical Modelling, 3(5), 391–405. doi: 10.1016/0270-0255(82)90038-0.

Wright, J. A., Loosemore, H. A., and Farmani, R. (2002). Optimization of building thermal design and control by multi-criterion genetic algorithm. Energy and Buildings, 34(9), 959–972. doi: 10.1016/S0378-7788(02)00071-3.

Xin, B., Chen, L., Chen, J., Ishibuchi, H., Hirota, K., and Liu, B. (2018). Interactive multiobjective optimization: A review of the state-of-the-art. IEEE Access, 6, 41256–41279. doi: 10.1109/ACCESS.2018.2856832.

Xu, Y., Yan, C., Liu, H., Wang, J., Yang, Z., and Jiang, Y. (2020). Smart energy systems: a critical review on design and operation optimization. Sustainable Cities and Society, 62, 102369. doi: 10.1016/j.scs.2020.102369.

Yammani, C., and Prabhat, P. (2018). Collaborative demand response in smart electric grid with virtual system operator. IET Smart Grid, 1(3), 76–84. doi: 10.1049/iet-stg.2018.0023.

Yan, Z., Zhou, Z., Liu, J., Wen, T., Sang, X., and Zhang, F. (2020). Multiobjective optimal operation of reservoirs based on water supply, power generation, and river ecosystem with a new water resource allocation model. Journal of Water Resources Planning and Management, 146(12), 05020024. doi: 10.1061/(ASCE)WR.1943-5452.0001302.

Yang, R., and Wang, L. (2012). Multi-objective optimization for decision-making of energy and comfort management in building automation and control. Sustainable Cities and Society, 2(1), 1–7. doi: 10.1016/j.scs.2011.09.001.

Yu, W., Li, B., Jia, H., Zhang, M., and Wang, D. (2015). Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design. Energy and Buildings, 88, 135-143. doi: 10.1016/j.enbuild.2014.11.063.

Zhang, Q., and Li, H. (2007). MOEA/D: A multiobjective evolutionary algorithm based on decomposition. IEEE Transactions on Evolutionary Computation, 11(6), 712–731. doi: 10.1109/TEVC.2007.892759.

Zhao, X., Gao, W., Qian, F., and Ge, J. (2021). Electricity cost comparison of dynamic pricing model based on load forecasting in home energy management system. Energy, 229, 120538. doi: 10.1016/j.energy.2021.120538.

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