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Continuous Optimization

Dynamic multi-objective heating optimization

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Abstract

We develop a multicriteria approach to the problem of space heating under a time varying price of electricity. In our dynamic goal programming model the goals are ideal temperature intervals and the other criteria are the costs and energy consumption. We discuss the modelling requirements in multicriteria problems with a dynamic structure and present a new relaxation method combining the traditional ϵ-constraint and goal programming (GP) methods. The multi-objective heating optimization (MOHO) application in a spreadsheet environment with numerical examples is described.

Keywords: Interval goal programming; Multicriteria optimization; Residential heating; Spreadsheet modelling

1. Introduction

In this paper we introduce an application of multicriteria optimization from our everyday environment. The problem is to optimize the indoor temperature, i.e., thermal comfort in a residential house. The problem is methodologically quite interesting as decision support is clearly needed due to the system dynamics and the necessity to tradeoff preferences which are costs and comfort over time. The definition of comfort is a complex issue in itself [13]. This paper develops a new goal programming (GP) approach. The dynamics of the problem arises from three factors: the house acts as a heat storage, the price of electricity is time varying and the outdoor temperature changes over the day. The criteria included in the model are the total heating costs, the energy consumed and the living comfort implicitly defined through the levels and variations of hourly indoor temperature. The model is implemented on a spreadsheet application multi-objective heating optimization (MOHO) [18] which is used to illustrate the solutions. A setting of this kind is a realistic one both for small residential and large commercial electricity users. With the introduction of deregulated energy markets [37] the possibilities of a consumer to be offered innovative pricing contracts is increasing. In the old regulated environment there could exist national legislation determining the acceptable types of time varying prices (such as time of use, TOU). Today the situation has changed, at least in the Nordic countries, where the distribution and

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selling of electricity are separated by law. You can buy electricity from any supplier and not only from your local distributor [19,37]. There can be brokers who can have different kinds of dynamic pricing policies to offer. Customers are also willing to subscribe to such policies and act reactively in their use of electricity. It is this setting which is of interest in the model presented here. The implementation described remains still a research effort which is not yet available commercially. However, it has successfully been tested with consumers by the utility of Helsinki Energy. There are no technical reasons why a system like this could not be implementable in real life. In fact, the authors do believe that this will be an optional direction for future pricing policies as part of the so-called smart house concept. Environmental issues are also related to the avoidance of demand peaks. They are often met with more polluting reserve generation units. Naturally, policies of this kind become increasingly interesting in larger commercial and community buildings.

2. Goal programming

GP is a widely used [47] multicriteria method originally presented in 1955 by Charnes and Cooper [9]. The name GP was introduced only later in a book from 1961 [7], where it was described as an extension to linear programming (LP). Today there are new textbooks, e.g., by Ignizio [21,22]. Some modelling and critical issues of GP are discussed in [41] and more recent developments can be found in [4,51].

In the multicriteria setting the special characteristic of GP models is the way the decision criteria are dealt with. Instead of a direct evaluation of the criteria outcomes, GP models explicitly introduce the desired target values, goals, for each criterion and optimize the deviations of criteria outcomes from these goals. The solution depends on the metrics used for the deviations as well as the method of weighting of the different goals. There are two common weighting methods. The first one is the fixed ordering of goals. In practice this is implemented by searching a lexicographic minimum of the ordered deviations vector [23]. The second one is the use of relative weights on goals and the minimization of the weighted sum of goal deviations [8]. Sometimes also the minimization of the maximum deviation is used as suggested by Flavell [14]. Using different unattainable goals and weights one can generate the entire Pareto frontier under convexity assumption of the feasible criteria set [36]. The GP approach of multicriteria problems has received increasing interest due to its modelling flexibility and conceptual simplicity.

2.1. Dynamic goal programming

Many multicriteria problems are by nature dynamic in the sense that they introduce variables describing the states of the system and control, i.e., decision, variables affecting the states through the system dynamics. Examples of such problems arise e.g. in water resource management [32,50,54], production planning [12] and control problems [49]. Optimal multivariable control (for references see e.g., [29,31]) is by definition a multicriteria problem. However, it is surprising that very few papers have suggested using GP in dynamic situations. The works of Levary in [28,29] introduce goal values for criteria in each state and give the necessary conditions for linear multi-goal discrete optimal control problems. Trzaskalik in [55] uses priority ordering of goals to solve the dynamic multicriteria problem. Kumar et al. [26] apply dynamic goals in flexible manufacturing systems. Sastry et al. [45,46] give goals for each criteria in each stage and use priority order of criteria in each stage to solve the control problem. They extend the approach by defining goals as fuzzy sets and replace deviations from goals with membership functions. Caballero et al. [3] introduce dynamic goal values on the accumulated values of objectives and describe a lexicographic solution algorithm.

3. Dynamic multicriteria problems and interval GP

This paper discusses modelling approach needed when dynamics are involved in multicriteria problems and provides a real life example of such problem, namely heating optimization. In particular we study the use of intervals in the definition of the goals. Already in [6,10] and in the survey paper of Charnes and Cooper [8] the possibility of using goal intervals, i.e., goal sets, was presented. Some related early applications include financial planning [27] and water reservoir management [5]. However, it was only recently that the use of interval goals to model the decision maker's (DM's) preferences was more strongly brought up by Martel and Aouni [34,35]. They suggest not only the use of interval goals as a way to overcome the imprecises knowledge of DMs goals, but also to model the DMs satisfaction asymmetrically and nonlinearly as a function of the observed deviations. Tamiz and Jones [53,52] apply the idea with goal points, but using increasing or decreasing piecewise linear penalties. Vitoriano and Romero [56] point out a possibility of biased results with piecewise linear penalties and suggest as a compromise a weighted sum of maximum and linear deviations. A more general modelling technique to also allow several *separated* interval goals for a single criterion without the need to use 0-1 decision variables is given by Li and Yu [30]. Separated interval goals enable to generate models of preferences, where e.g., first a narrow interval criteria values are preferred. If these cannot be achieved then another wider interval will be accepted. Regardless of the theoretical developments, so far, interval goal models have not been commonly used in applications.

Fig. 1 illustrates the use of intervals in GP in a two-dimensional case. As seen in Fig. 1 the deviation measures from the feasible decision set S need to be different for a goal point and for a set of interval goals.

This issue is discussed by Inuiguchi and Kume [24] and they introduce four different GP models with interval technical coefficients and goals.

The need to use interval goals can originate from different sources. The specification of goal points can be too restrictive when we have strongly related constraints. For example, the system dynamics can sometimes make it hard to reach goal points. The usefulness of interval goals can also arise from the DM. He can have impreciseness or ambiguity in his ability to express his personal preferences [42–44].

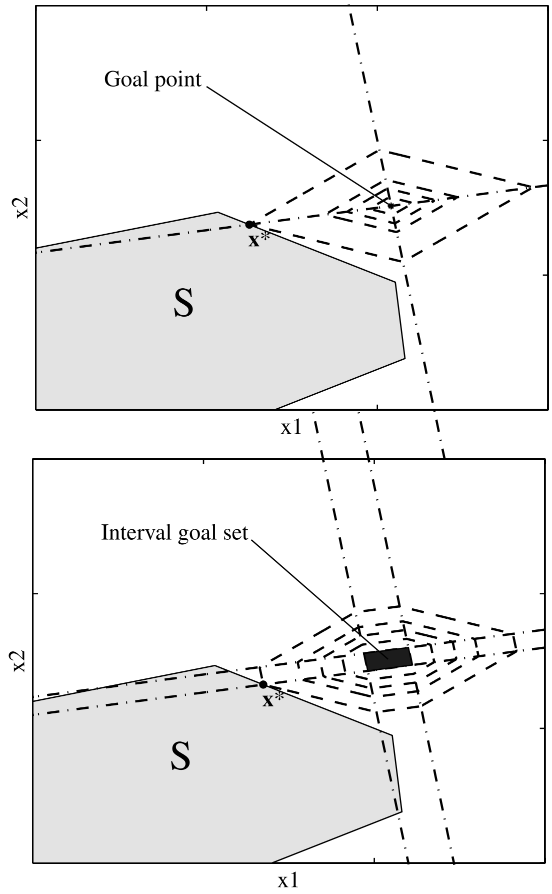


Fig. 1. Examples of linear deviation measures for a goal point and an interval goal set. The feasible decision space is S and optimal solutions are marked by x^*.

The goal values for the criteria are important for the DM, but in certain dynamic problems time should be taken explicitly into account [25], e.g. by discounting as in long-term planning [1]. For this same reason methods based on pairwise comparisons of all the individual criteria at each time stage may become exhaustively laborious for the DM. In such situations problems can often be tractable by a dynamic goal or a interval GP approach.

4. GPϵ method

In multi-objective analysis one often wants to study the effects of relaxing some goal constraints.

This is particularly relevant in dynamic GP where the DM needs to provide goal values for each criterion at each stage. Therefore, we will introduce a method combining the ϵ-constraint method of Haimes [15,16] and GP in the heating problem. For simplicity, we consider minimization of all the criteria, i.e.,

$$\min_{x\in S} \quad \{f_1(x), f_2(x), \ldots, f_k(x)\}, \tag{1}$$

where $x = (x_1, x_2, \ldots, x_n)$ is the n-dimensional vector of decision variables, $f_i(x)$ are given real valued criteria functions and $S \subset \mathbb{R}^n$ is a nonempty feasible set of decision variables. We recall that a feasible solution $x^* \in S$ is a Pareto optimal or *efficient* to (1), if there exists no other feasible solution that would make at least one criterion better while maintaining other criteria at least as good as they were, i.e., $x^* \in S$ is a *Pareto optimal solution* to (1), if and only if there does not exist $x \in S$, s.t. $f_i(x) \leqslant f_i(x^*)$, $\forall i = 1, \ldots, k$, and $f_j(x) < f_j(x^*)$ for at least one j.

The idea of relaxation is to convert some of the criteria into constraints by giving them upper limits as in the ϵ-constraint method and specify goal values for the rest. This results into an ϵ-constrained GP problem (GPϵ):

$$\begin{aligned} \min_{x\in S, d} \quad & \sum_{i\in G} w_i d_i \\ \text{s.t.} \quad & f_i(x) - d_i \leqslant g_i \quad \forall i \in G, \\ & f_j(x) \leqslant \epsilon_j \quad \forall j \in E, \\ & d_i \geqslant 0 \quad \forall i \in G, \end{aligned} \tag{2}$$

where E is a nonempty subset of criteria indexes, i.e., $E \subset K = \{1, \ldots, k\}$, $G = K \setminus E$, g_i are goal values, d_i are goal deviation variables and all weights w_i are positive.

Fig. 2 illustrates the method in a two criteria case. Let ϵ_1 be an upper bound for the criterion f_1. A goal for the criterion f_2 is either a or b. If the goal a is used, the optimal solution for corresponding GPϵ problem is the Pareto point indicated by z_a^*. This solution is unique. On the otherhand, if the goal b is used, the solution is the non-Pareto line segment pointed by z_b^*. This solution is not unique. The following theorem proves that Pareto optimal points are produce by the GPϵ method, if optimal solutions for the corresponding GPϵ problems are *unique*.

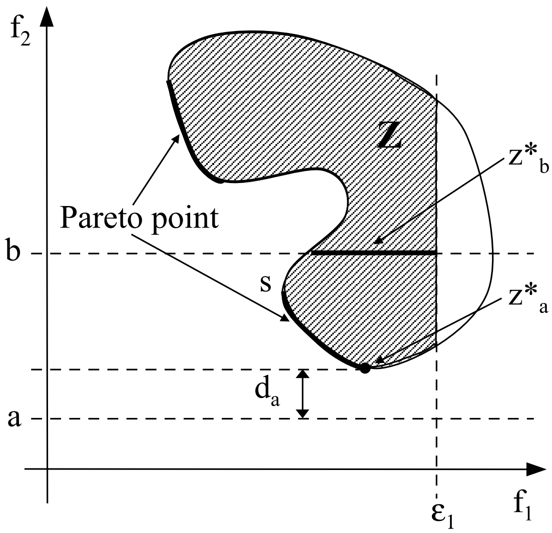


Fig. 2. An illustration of the GPϵ method. The upper limit for criterion f_1 is set to ϵ_1, which constraints the feasible criteria space Z into the gray area. The scalars a and b are two different goals for criterion f_2. The related solutions of the GPϵ problem are the point z_a^* for goal a and the line segment z_b^* for goal b.

Theorem 1. *If x^* is a unique optimal solution to GPϵ with $w_i > 0$, $\forall i \in G$, then x^* is a Pareto optimal solution to* (1).

Proof. If x^* is not a Pareto optimal solution to (1), then there exists $x \in S$ s.t. $f_i(x) \leqslant f_i(x^*), \forall i$ and $f_l(x) < f_l(x^*)$ for at least one index $l \in K$. There are two possible cases, either $l \in E$ or $l \in G$. The optimal deviation values are $d_i^* = \max\{0, f_i(x^*) - g_i\} \geqslant 0$. If $l \in E$, then $f_i(x) - d_i^* \leqslant f_i(x^*) - d_i^* \leqslant g_i$, $\forall i \in G$. It also implies $f_j(x) \leqslant f_j(x^*) \leqslant \epsilon_j$, $\forall j \in E, j \neq l$ and $f_j(x) < f_j(x^*) \leqslant \epsilon_j$. Therefore all the constraints of the GPϵ are satisfied and the value of the objective function in GPϵ remains the same. This contradicts the assumption of x^* being a *unique* optimal solution to GPϵ.

Let us define $\rho_i = f_i(x^*) - f_i(x) > 0$ and $d_i' = \max\{0, d_i^* - \rho_i\} \geqslant 0$. If $l \in G$, there are two possible cases either $d_l' < d_l^*$ or $d_l' = d_l^*$. In both cases it holds $0 \leqslant d_i' \leqslant d_i^*$, $\forall i \in G$, which gives $f_i(x) - d_i' \leqslant f_i(x^*) - d_i' \leqslant g_i$, $\forall i \in G$ implying that constraints of the GPϵ are satisfied in x. The case $d_l' < d_l^*$ implies $\sum_{i\in G} w_i d_i' < \sum_{i\in G} w_i d_i^*$, since $w_i > 0$ $\forall i \in G$, which contradicts x^* being an optimal solution to GPϵ. The case $d_l' = d_l^*$ implies $\sum_{i\in G} w_i d_i' \leqslant \sum_{i\in G} w_i d_i^*$, which contradicts x^* being a *unique* optimal solution to GPϵ. $\square$

If GPϵ problem is a linear programming problem, that is the criteria and the constraint functions are linear, we can use reduced costs of the GPϵ problem to check the uniqueness. If all the reduced costs of the nonbasic variables in the optimal solution Simplex table are strictly negative, the uniqueness of the solution is guaranteed by LP theory [48]. In the case where uniqueness does not hold the Pareto optimality of the solution can be restored with the general Pareto optimality test of Benson [2]:

$$\begin{aligned} \max_{x\in S} \quad & \sum_{i=1}^{k} \epsilon_i \\ \text{s.t.} \quad & f_i(x) + \epsilon_i = f_i(x^*) \quad \forall i = 1,\ldots,k, \\ & \epsilon_i \geqslant 0. \end{aligned} \tag{3}$$

Let $\bar{x}, \bar{\epsilon}$ be the optimal solution for (3) then it can be proved (see [2]) that:

(a) If $\epsilon_i = 0, \forall i$, then x^* is a Pareto optimal solution for the MCP.

(b) If at least one $\epsilon_i > 0$, then x^* is not a Pareto optimal solution for the (1), but $\bar{x}$ is.

If an ϵ-constraint in GPϵ is too restrictive, there might be no feasible solution for GPϵ problem.

5. Multi-objective heating optimization

The objective of residential heating systems is to keep the indoor temperature within comfortable limits. The traditional control device is a thermostat which keeps the indoor temperature close to the preset level. However, if the price of electricity is time dependent, there is a possibility to save in heating costs by using the house as a heat storage. This leads to a multicriteria problem of maximizing the living comfort and minimizing the heating costs under a given price of electricity, such as the time-of-use (TOU) price [38–40]. The normal TOU pricing mechanisms have one or two periods of high prices during the day time. The use of TOU pricing is a way for the utility to manage its total load. It provides an incentive for the customers to shift load from the hours of peak consumption (see Fig. 3).

Another criterion to be considered in heating is the total amount of heating energy consumed. The minimization of the energy introduces an environmental goal in addition to the economic cost criterion.

5.1. System dynamics

The house acts as an energy storage and this creates the dynamics of the system. It is described

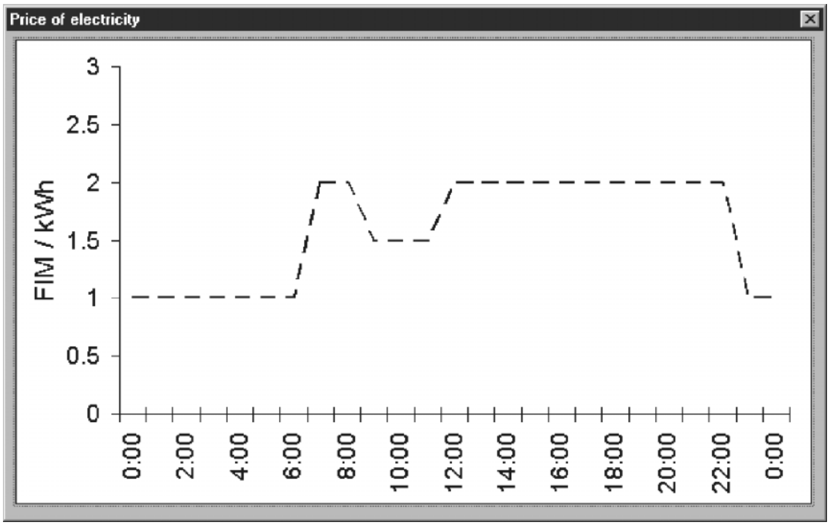


Fig. 3. The TOU price used in the examples.

by the state variable Q_i, which is the heat energy stored in the structures of the house at a time point i. The change in state depends on the previous heating power, q_i, and heat flow out of the house, θ_i:

$$Q_{i+1} = Q_i + \Delta t q_i - \theta_i, \quad i = 0, \ldots, N-1,$$

where N is the number of time points in the planning period. The heat flow is assumed to depend linearly on the difference between indoor temperature, T_i, and outdoor temperature, T_i^{out}, i.e.,

$$\theta_i = \alpha \Delta t (T_i - T_i^{\text{out}}).$$

Conversion of the state of the house to indoor temperature is made by using a measured heat capacity of the house, C, as $T_i = Q_i/C$, $(\beta = 1/C)$. The system equation of the house gives the next indoor temperature of the house depending on the previous outdoor temperature and heating power as

$$T_{i+1} = T_i + \beta \Delta t q_i - \alpha \beta \Delta t (T_i - T_i^{\text{out}}), \quad i = 0, \ldots, N-1. \tag{4}$$

5.2. The heating optimization problem

The objective function in heating problem could be any of the following:

$$\begin{aligned} J_1 &= \sum_{i=0}^{N-1} p_i q_i \quad \text{(heating costs)}, \\ J_2 &= \sum_{i=0}^{N-1} q_i \quad \text{(heating energy)}, \\ J_3 &= \sum_{i=0}^{N-1} |T_i - T_i^{\text{ideal}}| \\ &\quad \text{(deviation from the ideal temperature)}, \end{aligned} \tag{5}$$

where p_i is the hourly price of the electricity and T_i^{ideal} is the hourly ideal indoor temperature specified by the DM. Thermal comfort is a subjective feeling [13]. We will assume that the DM can specify a desirable interval of comfort for the indoor temperature for each hour of the day. We need to have a periodicity constraint $T_0 = T_N$ requiring the indoor temperature of the first hour of the day to be the same in the following day. One usually also specifies lower and upper limits for the indoor temperature, l_i, u_i, respectively. The maximum heating capacity of the heating system, q, is a property of the house. The optimal heating problem is thus defined:

$$\begin{aligned} \min \quad & J \\ \text{s.t.} \quad & (4) \quad \text{(system equation)}, \\ & T_0 = T_N \quad \text{(periodicity constraint)}, \\ & l_i \leqslant T_i \leqslant u_i, \quad i = 0, \ldots, N-1 \\ & \quad \text{(lower and upper limits)}, \\ & 0 \leqslant q_i \leqslant q, \quad i = 0, \ldots, N-1, \end{aligned} \tag{6}$$

where indoor temperatures T_i, $i = 1, \ldots, N$, are state variables and the initial indoor temperature T_0 and heating powers q_i, $i = 0, \ldots, N-1$, are the decision variables.

Using single objective functions J_1 or J_2 in (6) makes it in a LP problem with $2N + 1$ variables and $N + 1$ equality constraints with additional upper and lower limits for the variables. The objective function J_3 requires the addition of ideal indoor temperature deviation variables and enlarges the problem into $4N + 1$ variables and $2N + 1$ equality constraints with the nonnegativity constraints also for the deviation variables.

5.3. Relaxation of temperature limits

We use hard limits for the indoor temperature in problem (6). These limits can also be treated as flexible decision variables. In other words the original temperature limits are taken as interval goals. In this case we formulate a multicriteria problem e.g., minimizing the total heating costs J_1 and minimizing heating energy J_2 and maximizing comfort, i.e., minimizing the deviations from the original upper temperature limits. The problem is approached by the GPϵ method as in (2). We start by stating a hard upper limit for the heating costs and heating energy and a zero goal for the deviations. The resulting GPϵ problem is

$$
\begin{aligned}
\min \quad & (1-\lambda)\left(\sum_{i=0}^{N-1}(d_i^- + d_i^+)\right) + \lambda\rho \\
\text{s.t.} \quad & J_1 \leqslant (1-\epsilon)J_1^* \quad (\epsilon\text{-constraint for costs}), \\
& J_2 \leqslant E_{\max} \quad (\epsilon\text{-constraint for energy}), \\
& u_i + d_i^- - d_i^+ = u_i^0 \quad (\text{goal constraint}), \\
& d_i^- + d_i^+ \leqslant \rho, \quad i = 0,\ldots,N-1 \\
& \quad (\text{maximum deviation}), \\
& (4) \quad (\text{system equation}), \\
& T_0 = T_N \quad (\text{periodicity constraint}), \\
& l_i \leqslant T_i \leqslant u_i \quad (\text{lower and upper limits}), \\
& 0 \leqslant q_i \leqslant q, \\
& \rho, d_i^-, d_i^+ \geqslant 0, \quad i = 0,\ldots,N-1,
\end{aligned} \tag{7}
$$

where the new decision variables are the deviations, d_i^-, d_i^+, maximum deviation, ρ, and the new upper limits, u_i, $i = 0,\ldots,N-1$. The scalar ϵ-constraint for costs is fixed beforehand by asking the desired additional percentage savings, e.g. $\epsilon = 0.05$ (5%) in the reference value J_1^*. The limit for energy consumption per day $E_{\max}$ also needs to be given. The goal constraint measures the deviations from the original upper limits, u_i^0, and the maximum deviation constraint identifies the maximum of these. The objective is to minimize both the sum of deviations and the maximum deviation from the original upper limits. Minimizing only the maximum deviation could end up in an equal deviation from all the original limits, whereas the minimization of the sum of deviations could result in a large deviation from one or two limits only. Therefore we use a weighted sum of these deviation measures in order to reach balanced modifications of the upper limits to achieve the desired level of the criterion J_1 or J_2. Here the weight coefficient λ is taken to be 0.4.

Problem (7) is used to support the tradeoff of the living comfort for costs savings, by indirectly asking the DM to specify the desirable level of the heating costs. It should be noticed that the problem is not always feasible, since here only the upper limits of the indoor temperature are relaxed. The maximum heating power of the house can also become a limiting factor as more cost savings are required.

6. The spreadsheet application MOHO

The overall setting for the heating is shown in Figs. 4 and 5 shows the interfaces of the related spreadsheet application MOHO. The house parameters consist of the dynamic heat transfer model of the house and the maximum heating power. The variable planning parameters include electricity price for each hour and the outdoor temperatures at five time points.

Before the optimization takes place the DM needs to give his or her preferences. In the first step the DM specifies his indoor temperature limits. Next, the DM selects to minimize either the heating costs or energy consumption. If the solution is infeasible, the temperature limits might be too tight and a respecification of the limits is needed. The iteration on the limits need to be continued until a feasible solution is found. The results show costs and energy used as well as the indoor temperature and heating profiles. If the DM does not like the solution, a respecification of the limits is possible or the DM can continue by relaxing the indoor temperature limits. The relaxation process seeks to improve the value of the heating costs. The DM states the percentage improvements to which he aims at and the process is continued until the DM is satisfied with the solution.

MOHO is implemented in MS Office 95 Excel spreadsheet program using Excel's own Visual Basic programming language. The LP problems (6) and (7) are solved by the Excel Solver. The Pareto efficiency of the results is checked by the method of Benson described in (3).

The main window of MOHO is shown in the middle of Fig. 5. The buttons open different interface windows to set the outdoor temperature forecasts and preferences, the optimization problem and to see the results.

Currently MOHO has adjustable parameters for five different houses. The houses can also be visualized by photos (a). The outdoor temperature forecasts in window (c) are given at five different time points. The DM gives the ideal indoor temperature limits in window (b). After the minimization of the heating costs or the energy consumption MOHO displays the resulting hourly indoor temperatures in window (d) and the heating

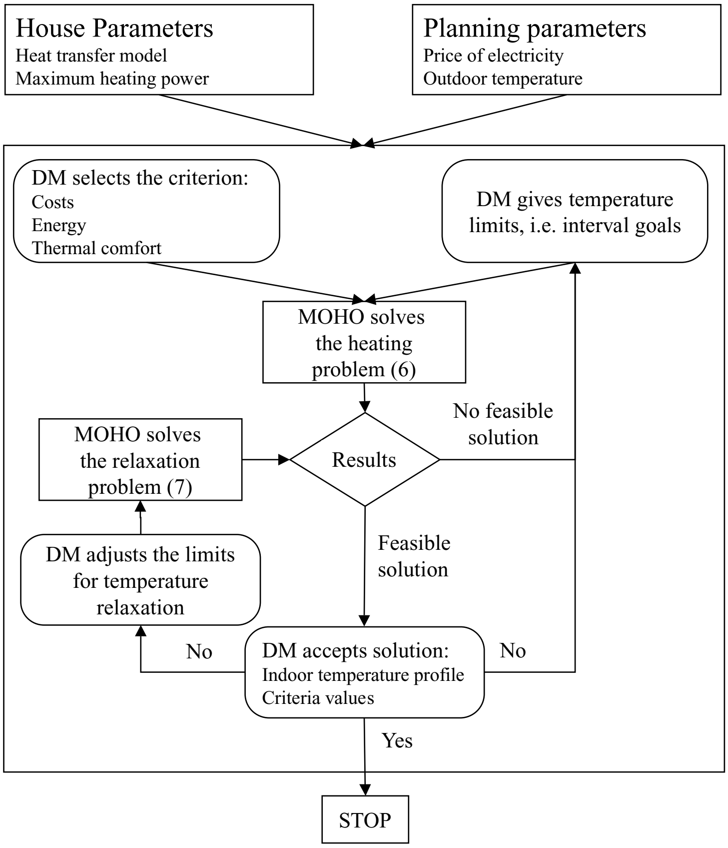


Fig. 4. The DMs multi-objective GP setting when using MOHO software.

strategy in window (e). The heating costs and the total energy consumed are displayed in the main window. The results are always also given for the reference problem in which a constant indoor temperature of 20 °C is maintained. This gives the DM an estimate of the gains achieved by taking the dynamics into account.

Next we describe the use of MOHO for two different houses (for parameters see Table 1). The floor area of both houses is over 100 m^2. House 1 is made up of rock material with a brick surface and therefore has a larger heat capacity than House 2 which is made up of wood. On the other hand House 2 has a smaller heat dissipation coefficient which refers to a better insulation. The maximum heating capacity is about the same in both houses. We assume that there is a cold winter day during which the temperature changes between -15 and -10 °C as shown in Table 2. The TOU electricity price has peak periods between 7:00–9:00 and 12:00–23:00 as seen in Fig. 6.

The solution proceeds so that DM first requires the indoor temperature to stay between 20 and 22 °C and starts by minimizing the heating costs. The solution is shown in Fig. 6. We see that heating is on during the off peak hours in order to store heat energy before the start of the peak price hours. At the start of the peak price period heating is first turned off and then the indoor temperature will start to decline until the lower bound is reached and then heating is started again. Next the DM allows the lower limits of the indoor temperature to drop during the working hours 9:00–17:00 by setting the lower bound to 17 °C. Fig. 7 shows the results after the reoptimization for House 2. House 2 will save more in heating costs but the solution

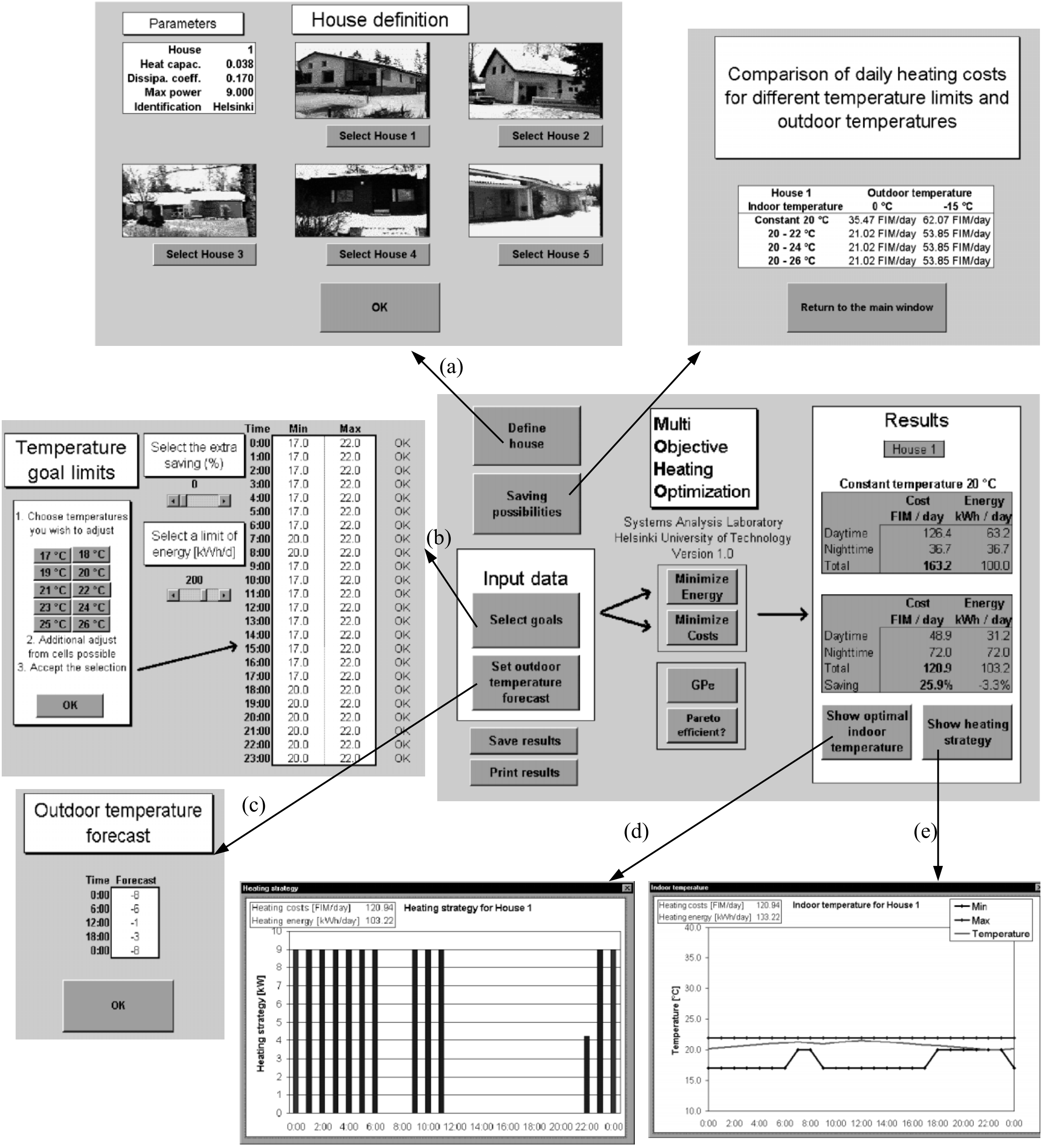


Fig. 5. The MOHO software. Description of houses (a), setting of temperature goals (b), outdoor temperature forecasts (c), optimal indoor temperature (d) and optimal heating strategy (e).

for House 1 will not change since none of the original lower limits were active in the solution during the working hours. As shown in Fig. 7 two of the indoor temperature upper limits are active

Table 1
Description and parameters of the houses

	House 1	House 2
Type of the house	Two unit house	Single family house
Building material	Insulated rock with a brick surface	Wood
Floor area (m^2)	170	139
Number of floors	2	1
Heating equipment	Ceiling and floor radiators	Ceiling and floor radiators
α (kW/°C)	0.170	0.077
β (°C/kW h)	0.038	0.380
Heating capacity (kW)	9.0	8.7

Table 2
Outdoor temperature forecasts

Time	0:00	6:00	12:00	18:00	24:00
(a) Cold winter day (°C)	−15	−12	−10	−10	−15
(b) Normal winter day (°C)	−8	−6	−1	−3	−8

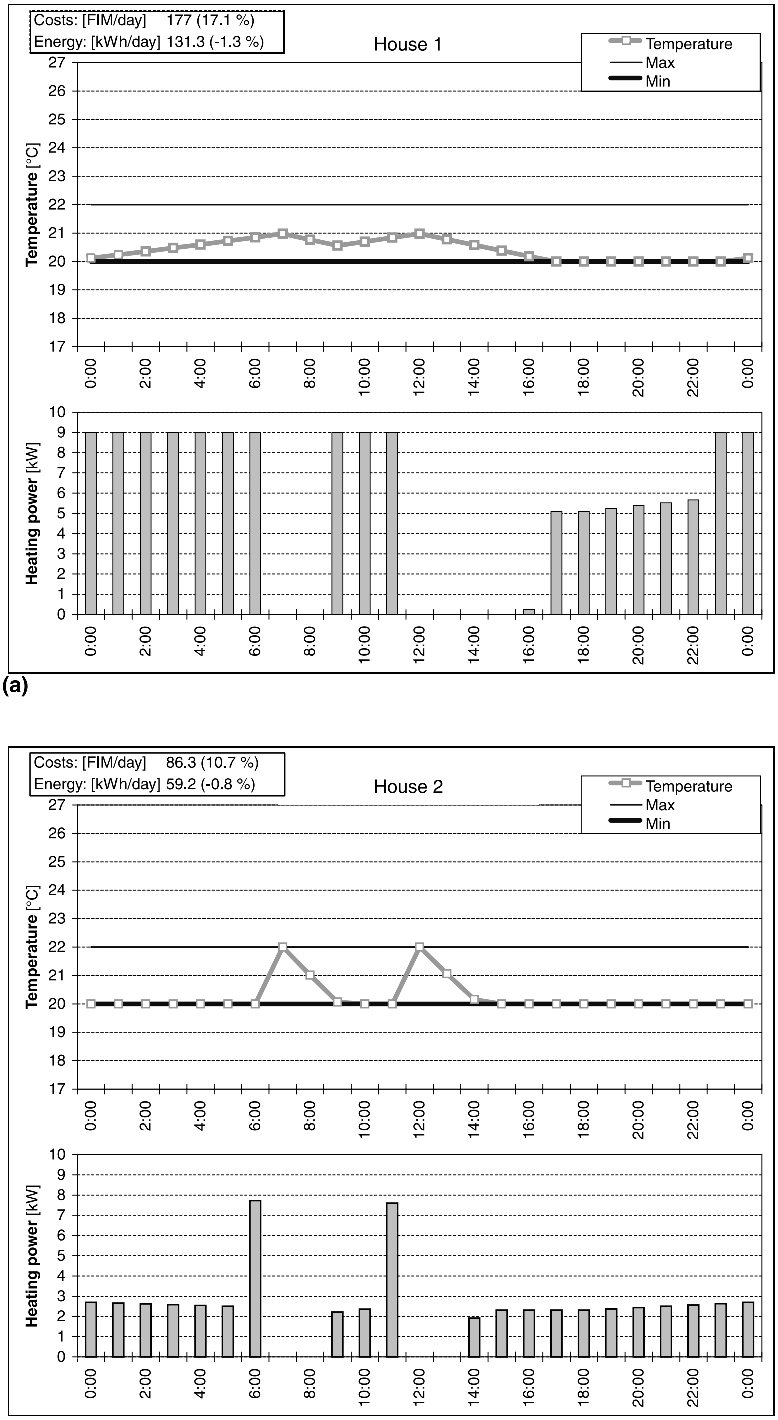
in House 2. This enables the DM to use problem (7) to tradeoff living comfort to cost savings. In House 1 relaxation is not possible, since none of the indoor temperature upper limits is active.

One way to analyze the properties of the solution is to plot the maximum deviation from the given ideal intervals, heating costs and heating energy in the same picture as in Fig. 8. These solutions, which are produced by the GPϵ method by relaxing the deviations from the upper temperature limits on a normal winter day as in Table 2, show what one gains by giving up comfort. From the figure, we see that the extreme solutions are practically not feasible, since the maximum temperature rises up to 32°.

7. Conclusions

We show how the space heating of a house can be formulated as a dynamic multicriteria optimization problem, and that one can successfully use the spreadsheet as a modelling environment for finding the solution. Instead of directly dealing with the tradeoffs between criteria, we suggest a stepwise procedure. It starts by first minimizing the costs or energy consumption and continues then by respecifying the goal or relaxing the temperature limits. We present a new GPϵ method combining the ϵ-constraint method and GP to support the relaxation of the temperature limits. Our implementation of this relatively demanding optimization model in the spreadsheet Excel also encourages the use of spreadsheets as a prototyping modelling environment [33]. One of the immediate direct uses of the present software is teaching and customer information. It can help the consumers understand the dynamics of the house as a heat storage. Often, customers under TOU tariff ignore the dynamics and set their setting for indoor temperature to coincide with the changes in price in their TOU tariff.

Such multicriteria models for optimizing comfort in space heating systems could easily be implemented in home automation systems working according to the home owner's preferences [11,38,39]. A similar problem is the cooling of a house in hot climates. Equivalent models can be applied to cooling by considering the heating power as cooling power. The automation system needed to carry out the optimization could be provided by the utility and the solution could be transferred to the home automation devices by means of modern telecommunication techniques, e.g., by using the power lines as a channel. The arrangement where consumers define their dynamic preferences by means of a tradeoff parameter and the utility takes care of the optimization should be an attractive option. The consumer has full control of the decision on house heating while the utility provides the service of computing the solution and implementing it. In the new deregulated setting this service could equally well be provided by an intermediary i.e., a broker, see e.g.,



(a)

(b)

Fig. 6. Minimum heating cost solutions for House 1 (a) and House 2 (b) under a TOU price of electricity and for a cold winter day.

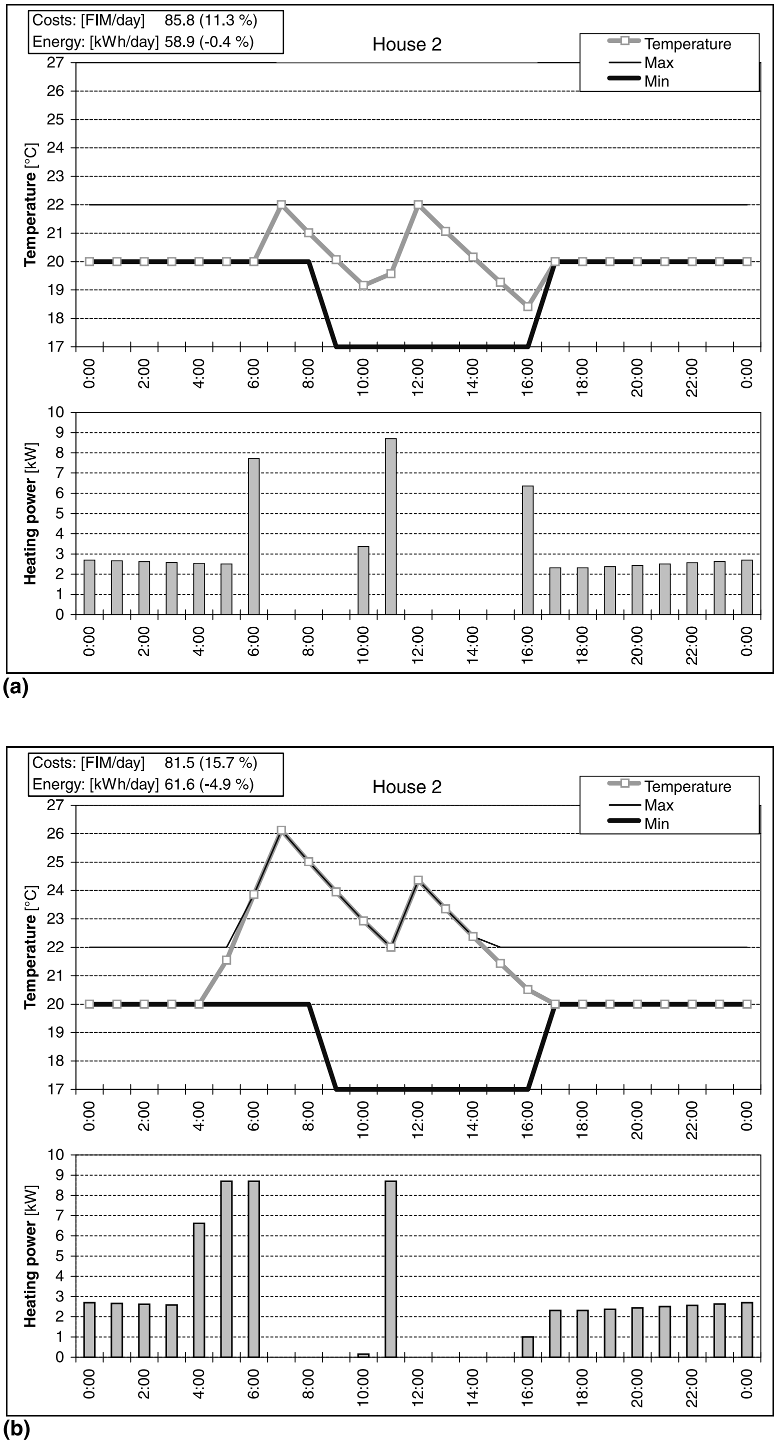


Fig. 7. Solution for House 2 with time-dependent temperature goals (a). The solution with relaxed upper temperature limits (b) gives about 5% lower heating costs than the initial solution.

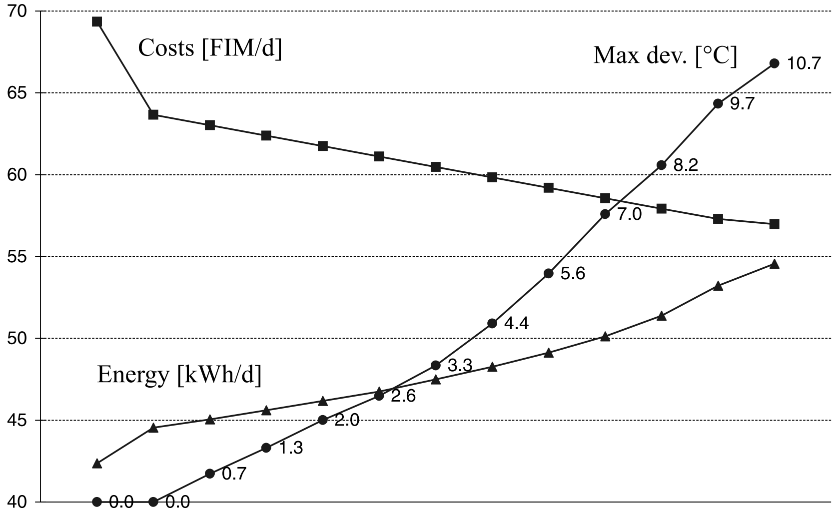


Fig. 8. Solutions when the upper temperature limits are relaxed progressively as in Fig. 7.

[19]. One can also consider the use of this kind of models of consumer reactions to estimate the total effect of the responses of all the consumers of the utility on its load [17,20]. Such simulation analyses are already tested in models of the new deregulated electricity markets [37]. Simulated agents with multicriteria behavior [19,33] represent the reactions of different space heating consumer groups under different time-dependent electricity prices. In this way the utility can better design its TOU tariffs.

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