A bi-level hybrid PSO – MIP solver approach to define dynamic tariffs and estimate bounds for an electricity retailer profit*

Extended Abstract†

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ABSTRACT

[1] With the implementation of dynamic tariffs, the electricity retailer may define distinct energy prices along the day. These tariff schemes encourage consumers to adopt different patterns of consumption with potential savings and enable the retailer to manage the interplay between wholesale and retail prices. In this work, the interaction between retailer and consumers is hierarchically modelled as a bi-level (BL) programming problem. However, if the lower level (LL) problem, which deals with the optimal operation of the consumer's appliances, is difficult to solve, it may not be possible to obtain its optimal solution, and therefore the solution to the BL problem is not feasible. Considering a computation budget to solve LL problems, a hybrid particle swarm optimization (PSO) – mixed-integer programming (MIP) approach is proposed to estimate good quality bounds for the upper level (UL) objective function. This work is based on [4].

KEYWORDS

Bi-level optimization, Hybrid algorithms, Dynamic tariffs, Demand response, Pricing problem, Electricity retail market.

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1 INTRODUCTION

Some approaches considering BL models have been proposed in the literature to define dynamic tariffs anticipating the consumer's decisions (e.g. [1,2]). We have also proposed BL approaches to model the interaction between an electricity retailer and consumers, where the LL (consumer's) problem is modelled as a MIP considering detailed physical information related with load operation and control [3,4]. In [4], the UL problem is tackled by a PSO algorithm and the LL problem is solved by an exact MIP solver. The consumer's model incorporates shiftable, interruptible and thermostatic loads. The modelling of the thermostat operation imposes a severe computational effort, which impairs obtaining the optimal solutions in an acceptable computation time by a state-of-the-art solver. This approach computes good quality estimates for the retailer's profit whenever a computational budget exists, helping to make sounder decisions in an adequate time frame.

2 BI-LEVEL MODEL

In the electricity retail market, the retailer defines dynamic tariffs and the consumers react by adjusting the energy consumption through the scheduling of load operation. Using a BL model to model this interaction, the UL objective function (Eq. (1)) is the maximization of the retailer's profit: difference between the revenue with the sale of energy to consumers (term (A)+(B)) and the cost of buying energy in the wholesale market (term (C)).

$$\max_x F = \underbrace{\sum_{i=1}^{I}\sum_{t\in P_i} x_i\left(b_t + \sum_{j=1}^{J} p_{jt} + \sum_{k=1}^{K} q_{kt} + s_t P_{AC}^{nom}\right)}_{\text{(A)}} + \underbrace{\sum_{l=1}^{L} e_l u_l}_{\text{(B)}} - \underbrace{\sum_{t\in T}\pi_t\left(b_t + \sum_{j=1}^{J} p_{jt} + \sum_{k=1}^{K} q_{kt} + s_t P_{AC}^{nom}\right)}_{\text{(C)}} \tag{1}$$

The planning period T is divided into I sub-periods of prices $P_i \subset T,\ i \in \{1,\dots,I\}$, disjoint and contiguous, for which the retailer should define the prices of electricity to be charged to the consumers, x_i (in €/kWh), with h being the unit of time the planning period is discretized into. The electricity prices are limited by minimum and maximum values for each sub-period P_i, and an average price for the whole planning period T to account for competition (UL constraints). Coefficients π_t in Eq, (1) are the prices of energy incurred by the retailer at time $t \in T$.

In each time t of the planning period T, the model considers the power required by a (non-controllable) base load – b_t, J shiftable appliances (whose operation cycles cannot be interrupted once initiated) – p_{jt}, K interruptible appliances – q_{kt}, and a thermostatic

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[1] It is a datatype.

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load, an air conditioner system – $s_t P_{AC}^{nom}$ (the binary variables s_t indicate the state on/off – 1/0). The retailer also defines L levels of power demand and the consumer pays e_l (in €) for the power level corresponding to the peak u_l, $l \in \{1, \dots, L\}$. The decision variables of the UL problem are the electricity prices x.

The LL problem arises as a constraint of the UL problem and the LL objective function (Eq. (2)) relates to the minimization of the consumer's electricity bill: the cost of the energy consumed by controllable and uncontrollable loads (term (A)) and the power cost (term (B)), and the costs resulting from the monetization of the positive and negative deviations (Δ_t^+ and Δ_t^-, respectively) of a temperature variable from a reference temperature (term (D)). Coefficients c^+ and c^- are the costs (in €/ºCh) incurred by the positive and negative temperature deviations, respectively. The terms (A) and (B) are the same as in Eq. (1).

$$\min f = (\mathrm{A}) + (\mathrm{B}) + \underbrace{\sum_{t \in T} (c^+ \Delta_t^+ + c^- \Delta_t^-)}_{(\mathrm{D})} \tag{2}$$

The consumer should specify comfort time slots in which each shiftable and interruptible load should operate, according to his preferences and routines, as well as minimum, maximum and reference indoor temperatures used for setting the air conditioner. The detailed LL constraints are presented in [4]. The decision variables of the LL problem are binary variables that indicate whether a load is "on" or "off" (and even in which operation stage it is) at each time, which define the auxiliary variables $p_{jt}, q_{kt}, u_l, \Delta_t^+, \Delta_t^-$ that appear in Eq.(1) and (2).

3 ALGORITHM AND RESULTS

The BL model is dealt with a hybrid approach, which uses a PSO algorithm to generate and evolve the UL variables. A special routine has been developed for repairing unfeasible pricing vectors considering the UL constraints. When the global best does not improve over a number of consecutive iterations, then the exploration capability is enhanced by introducing some turbulence in the population. For each UL pricing vector x, a MIP solver (Cplex) is called to solve the consumer's problem.

However, considering a realistic h (we have considered h =1/4 h) for the discretization of the planning period T, the LL problem may not be amenable to exact resolution, mainly due to the high computation effort associated with the modelling of the thermostatic load. For the dataset we have used, the LL problem has 839 binary variables, 535 continuous variables and 1700 constraints. The UL problem has 6 decision variables (since 6 periods have been defined for different prices) and 13 constraints.

If the LL problem cannot be solved to optimality, then it is not possible to guarantee the feasibility of the solution to the BL model. Thus, assuming that a computation budget exists, the aim is offering the retailer good quality estimates of bounds for his profit. For this purpose, an incremental strategy has been designed, starting by considering a reasonable computation time limit (15s) to solve each instantiation of the LL problem, storing κ solutions with the highest F value. At the final of the algorithm, the LL problem is solved again for the κ solutions with an increased time limit (60s). The output is the solution that presents the highest F. The algorithm is performed several independent runs and 10 selected solutions still undergo a deeper analysis, which consists in solving the LL problem with a longer time limit (5 min). This analysis aims at decreasing the MIP gap of the LL solution, so that good upper estimates (UE) of F can be obtained within a reasonable computation time. To obtain good lower estimates (LE), the characteristics of the problem are taken into account, namely the negative correlation between F and f. Accordingly, the discomfort component (C) is removed from the LL objective function and the LL problem is solved for the 10 prices of the solutions selected (with time limit of 5 min). This leads to minimum consumers' cost solutions and, consequently, to expected minimum retailer's revenues. Fig. 1 displays the intervals obtained for the retailer's profit in each of the 10 final solutions. For the corresponding UL prices and detailed statistics, please see [4].

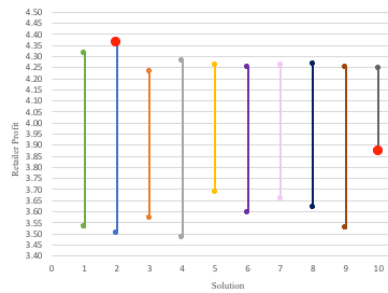

Figure 1: Retailer's profit intervals, [LE,UE], in the 10 final solutions.

This analysis indicates that solution 10 may be an adequate option for a risk-averse decision maker. Solutions 5 and 7 are also good options for a decision maker not willing to engage in a high risk, while solution 2 may yield a very good F value but with a higher risk of obtaining a low value.

4 CONCLUSIONS

The inclusion of a thermostatic load into the consumer's problem imposes a very high computational effort. Since the LL optimization problem arises as a constraint of the UL problem, only optimal solutions to the LL problem are feasible to the BL problem. We propose an incremental strategy based on a hybrid PSO – MIP solver approach to compute lower/upper estimates for the retailer's profit with a computational budget.

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