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A simulation-optimization approach for the household energy planning problem considering uncertainty in users preferences

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Abstract. Power supply is one of the basic needs in modern *smart homes*. Computer-aid tools help optimizing energy utilization, contributing to sustainable goals of modern societies. For this purpose, this article presents a mathematical formulation to the household energy planning problem and a specific resolution method to build schedules for using deferrable electric that can reduce the cost of the electricity bill while keeping user satisfaction at a satisfactory level. User satisfaction have a great variability, since it is based on human preferences, thus a stochastic simulation-optimization approach is applied for handling uncertainty in the optimization process. Results over instances based on real-world data show the competitiveness of the proposed approach, which is able to compute different compromise solution accounting for the trade-off between these two conflicting optimization criteria.

Keywords: smart cities; energy planning; mixed-integer programming; simulation; multiobjective optimization.

1 Introduction

The paradigm of smart cities aims at increasing resource efficiency in several daily activities that citizens perform in urban environments. In the case of energy management, this aim is not only related to the amount of energy consumed, but also to the infrastructure required to distribute the energy [3]. The capacity of this infrastructure is often conditioned by peak consumption, as it should be able to distribute the energy during the periods of high demand without producing power outages. However, if consumption of a certain area is remarkably unbalanced (having important variations along the day), this would required a large investment in infrastructure that will be idle the most of the time [10].

The introduction of time-of-use pricing in electricity bills for households is a major contributor to the overall efficiency of the electrical system, since it incentives citizens to have a smoother consumption patron, displacing the usage of electric devices from expensive peak hours to relatively cheaper off-peak hours. This behavior reduces the maximal instant power consumption of an urban area and, therefore, cuts back the required infrastructure investment to handle the peak and the risk of power outages [10]. However, usually off-peak hours, in which electricity is cheaper, are not preferred by users for using their appliances. This effect, which is known as inconvenience due to timing [1], can affect the well-being of the users. Therefore, there is a trade-off between both criteria, i.e., electricity cost and users satisfaction. Intelligent computer-aid tools may help users in the decision-making process of scheduling their deferrable devices [19].

This article proposes a novel mixed integer programming model for scheduling the deferrable electric appliances usage in households, which simultaneously considers minimizing the electricity cost and maximizing the users satisfaction. Users satisfaction measures to what extend the starting time and duration for appliances usage scheduled by the model match the users preferences–which is estimated through the analysis of historical data [4, 5, 22]. However, since this parameter can show certain variability between different days, a simulation-optimization resolution approach that considers this stochastic behaviour is devised. Therefore, the main contributions of the research reported in this work include: i) a compact mathematical formulation for the energy household problem, ii) the application of a stochastic resolution approach to consider uncertain users preferences, and iii) experimental evaluation over instances based on real-world data and analysis of the results.

The article is structured as follows. Section 2 presents the analysis of the main related works. The proposed mathematical formulation is outlined in Section 3. Section 4 describes the proposed simulation-optimization resolution approach. Section 5 describes the computational experimentation conducted to evaluate its effectiveness, and reports the numerical results for realistic problem instances. Finally, Section 6 formulates the conclusions and describes the main lines of future research.

2 Related work

Household energy planning has been considered as a complex problem in the related literature. The deterministic version (scheduling non-interruptible electric appliances) is associated with bin packing [16], a well-known NP-hard problem. Moreover, including uncertainty increases the complexity of the problem [17]. Several articles have considered uncertainty in this kind of problem. For a recent review, we refer to Lu et al. [18] for a comprehensive analysis of the topic and Liang and Zhuang [17], who focused on stochastic applications.

Uncertainty in energy household planning problems has been considered in several aspects. Chen et al. [6] considered uncertainties in the power consumed by the appliances and the renewable solar energy gathered by a photovoltaic array. A three-stages resolution process was proposed. First, a deterministic linear programming optimization model considering mean values for the appliances consumption and maximum solar power generation was solved. A stochastic procedure based on Monte Carlo simulation was applied to the resulting solution. The simulation considers different energy consumption rates of appliances and selects the consumption rate that minimizes the probability of shortcuts, which occurs when the overall consumption of electricity surpass a certain threshold value. Finally, an online adjustment of the previous (offline) solution was applied, which monitors the instant solar power generation and the consumption of appliances in real-time, compensating the household electric balance of the offline solution with a larger power storage in the battery or purchase from the grid. Hemmati and Saboori [12] proposed a particle swarm optimization algorithm to deal with uncertainty of photovoltaic panels in a similar problem. Assuming that the energy generated in the panels has a Gaussian probabilistic distribution, a Monte Carlo simulation was used each time the stochastic the stochastic function has to be evaluated to obtain a sample of the generation values.

Other researchers have used robust optimization, which aims at minimizing the impact of the worst-case scenario, considering that aleatory parameters have a bounded probabilistic distribution [1]. Jacomino and Le [13] presented a robust optimization approach to simultaneously minimize energy cost and maximize the comfort of users. They considered uncertainty in two aspects: the outdoor temperature and the solar radiation (related to weather forecast), that affect the energy to be consumed to satisfy the required indoor temperature, and users decisions related to not programmable services, i.e., despite the scheduled starting time and duration of the appliances the user can modified these conditions when actually using them. For handling uncertainty on users behaviour, a decomposition approach based on estimating the probability of occurrence of each scenario was used. Wang et al. [28] proposed a robust optimization approach for dealing with photovoltaic energy generation in household planning by using a mixed integer quadratic programming model, and Wang et al. [29] for dealing with uncertainty in hot water utilization and outdoor temperature that influences the usage of heating and air conditioning systems.

Other authors, although they have not consider uncertainty in their models, they have explored the trade-off that usually exists between electricity cost and users satisfaction through linear mathematical programming approaches -as it is performed in this work-. Among them, Yahia et al. [30] modeled a bi-objective problem considering these two objectives, which were combined by means of a linear weighted sum to form a unique objective function. They solved two single-household instances, i.e., a real South African case study and an artificial large instance, using LINGO. Additionally, they performed an extensive analysis of the sensitivity of the results to the modifications of certain parameters. The same authors expanded their work in [31] by considering as a third objective the reduction of the peak load. Moreover, in this last work they solved an instance considering several households simultaneously. They applied and compared three different multiobjective approaches: lexicographic optimization, normalized weighted sum and compromise programming.

This work contributes to the literature in several aspects. Firstly, a novel linear mathematical formulation of the household planning energy problem that explicitly considers users satisfaction as an objective function is presented. Approaches as such are not common in the related work [30]. Moreover, this is an improved mathematical formulation compared to the one presented in our previous work [20] for a similar conceptual model, having a smaller number of variables and restrictions. Secondly, this work considers stochastic users preferences which differentiates it to other linear programming applications in the related work [30, 31]. This leads to the final aspect that differentiates this work that is the application of the simulation-optimization Sample Average Approximation method to handle the uncertainty which has not been applied to this specific problem before.

3 Mathematical formulation

The household energy planning problem addressed in this article aims at reducing expenses of electricity in households while enhancing users satisfaction. This last objective was estimated by considering in which part of the day users prefer to use the appliances (inferred from historical data). Then, the mathematical formulation considers the following elements:

Sets:

- a set of users $U = \left(u_1 \dots u_{|U|}\right)$, each user represents a household;
- a set of time slots $T = \left(t_1 \dots t_{|T|}\right)$ in the planning period;
- sets of domestic appliances $L^u = \left(l_1^u \dots l_{|L|}^u\right)$ for each user u;

Parameters:

- a penalty term ρ^u applied to those users that surpass the maximum electric power contracted;
- a parameter D_l^u that indicates the average time of utilization for user u of appliance $l \in L^u$;
- a parameter C_t that indicates the utilization cost (per kW) of the energy in time slot t;
- a parameter P_l^u that indicates the power (in kW) consumed by appliance l;
- a binary parameter UP_{lt}^u that is 1 if user u prefers to use the appliance $l \in L^u$ at time slot t, 0 in other case;
- a parameter E^u that indicates the maximum electric power contracted by user u;
- a parameter E^{joint} that indicates the maximum electric power that the (whole) set of users U are allowed to consume;

Variables:

- a binary variable x^u_{lt} that indicates if user u has appliance $l \in L^u$ turn on at time slot t;
- a binary variable δ^u_{lt} that indicates if the appliance $l \in L^u$ of user u is turn on from time slot t up to a period of time that its at least equal to D^u_l;
- a binary variable ψ^u_t that indicates if the user is using more power than the maximum power contracted E^u.
- a binary variable Ψ^u_t that indicates if the user is using more power than 130% of the maximum power contracted E^u .

The problem aims at finding a planning function $X = \{x^u_{lt}\}$ for the use of each household appliance that simultaneously maximizes the user satisfaction (given the users preference functions) and minimize the total cost of the energy consumed. The mathematical formulation is outlined in Eqs. (1)-(11).

$$\max F = \sum_{u \in U} \sum_{l \in L^u} \sum_{\substack{t_1 \in T \\ t \leq |T| - D^u_l}} \left(\delta^u_{lt_1} \left(\sum_{\substack{t_2 \in T \\ t_1 \leq t_2 < t_1 + D^u_l}} UP^u_{lt_2} \right) \right) \tag{1}$$

$$\min G = \sum_{t \in T} \sum_{u \in U} \left(\sum_{l \in L^u} x^u_{lt} P^u_l C_t + \rho^u \left(0.3\psi^u_t + 0.7\Psi^u_t\right) \right) \tag{2}$$

Subject to

$$\delta^u_{lt} \leq 1 - \frac{D^u_l - \left(\sum_{\substack{t_2 \in T \\ t \leq t_1 < t + D^u_l}} x^u_{lt_1} \right)}{D^u_l}, \ \forall\, u \in U, l \in L^u, t \in T \tag{3}$$

$$\sum_{t \in T} \delta^u_{lt} = n^u_l, \ \forall\, u \in U, l \in L^u \tag{4}$$

$$\psi^u_t \geq \frac{\sum_{l \in L^u} P^u_l x^u_{lt} - E^u}{\sum_{l \in L^u} P^u_l}, \ \forall\, t \in T \tag{5}$$

$$\Psi^u_t \geq \frac{\sum_{l \in L^u} P^u_l x^u_{lt} - 1.3E^u}{\sum_{l \in L^u} P^u_l}, \ \forall\, t \in T \tag{6}$$

$$\sum_{\substack{u \in U \\ l \in L^u}} P^u_l x^u_{lt} \leq E_{joint}, \ \forall\, t \in T \tag{7}$$

$$\psi^u_t \in \{0,1\}, \ u \in U \forall\, t \in T \tag{8}$$

$$\Psi^u_t \in \{0,1\}, \ u \in U \forall\, t \in T \tag{9}$$

$$\delta^u_{lt} \in \{0,1\}, \ \forall\, u \in U, l \in L^u, t \in T \tag{10}$$

$$x^u_{lt} \in \{0,1\}, \ \forall\, u \in U, l \in L^u, t \in T \tag{11}$$

Eq. (1) aims at maximizing the users satisfaction according to their preferences. Eq. (2) aims at minimizing the energy expense budget, which include the charge for energy consumption and the penalization for exceeding the maximum power contracted. Eq. (3) enforces δ^i_{lt} to be one when the length of time an appliance will be on is equal or larger than the required by the user. Eq. (5) enforces ψ^i_j to be one if the user exceeds the maximum power contracted. Eq. (6) enforces Ψ^i_j to be one if the user exceeds the maximum power contracted for more than 30%. Eq. (7) enforces that the joint electric consumption by the set of users do not surpass a certain threshold maximum power. This equation is included when users are part of the same housing unit, e.g., an apartment building. Eqs. (8)-(11) establishes the binary nature of the variables.

4 The proposed simulation-optimization resolution approach for the stochastic household energy planning

Real-world data shows that considering users preferences (UP) as a deterministic parameter does not adjust to reality [15]. Users satisfaction can be modelled more accurately if uncertainty is taken into account for preferences in the model. Therefore, this article develops a resolution approach that considers this stochastic behaviour.

4.1 Bi-objective optimization

In order to handle the biobjective nature of the optimization problem presented in Section 3, a weighted sum optimization approach is applied. The weighted sum is a traditional method in the multiobjective optimization literature which has extensively been used in many applications, including for the energy household related problems [1]. Applying this approach, Eqs. (1) and Eqs. (2) are jointly optimized with Eq. (12), where w_F and w_G are the relative weights given to each criteria by the decision-maker.

$$\max H = w_F \frac{F - F^{best}}{F^{best} - F^{worst}} - w_G \frac{G - G^{best}}{G^{worst} - G^{best}} \tag{12}$$

One of the main drawbacks of this method is to know the actual best and worst values of each objective within the set of non-dominated solutions which are used for normalization (i.e., F^{best} and G^{best}, F^{worst} and G^{worst} in Eq. (12), respectively). In this work, for addressing this issue, the procedure proposed in Rossit [24] and applied in Rossit et al. [25] is used. This is a two step procedure. In the first step, the best and worst values of each objective are approximated by solving the single objective problem of each of the criteria involved. These values, which are likely to be dominated [2], are improved in the second step of the procedure. In this second phase, these best and worst values are used in the weighted sum formula (Eq. (12)) along with a biased combination of weights. This is, two different problems are solved, one problem using $w_F >> w_G > 0$ and the other problem using $w_G >> w_F > 0$. Finally, from the solutions of these last two multiobjective problems, the new best and worst values are obtained.

4.2 Sample Average Approximation method for considering stochastic users preferences

Formally, in a stochastic optimization problem with a probabilistic objective function, the expected value of this function should be optimized. In the case of the formulation described in Section 3, if parameters UP are considered stochastic, Eq. (1) should be replaced by Eq. (13).

$$e = \mathbb{E}_{\mathbf{P}}\left[F\left(\mathbf{\Delta}, \mathbf{UP}\right)\right]. \tag{13}$$

In Eq. (13), $\mathbf{UP}$ is the random vector of the stochastic users preferences and $\mathbf{\Delta}$ is the vector of decisional variables δ described in Section 3. In order to optimize Eq. (13), all the possible realizations of vector $\mathbf{UP}$ with its corresponding probability should be considered. Taking into account that the model of Section 3 uses a finite set of time slots, the set of possible realizations of $\mathbf{UP}$ is also finite. Particularly, there are $|T|^{\sum_{u\in U}|L^u|}$ realizations of this vector, each one constituting a possible scenario for the stochastic problem. For example, consider an instance in which the day is split in intervals of 30 minutes, i.e., $|T| = 48$, there two users (households) and each user has only two appliances ($|L^{u_1}| = |L^{u_2}| = 2$). Then, the number of possible scenarios would be $48^4 = 5,308,416$.

For the cases in which the large number of scenarios of real-world instances makes impractical to compute the exact expected value of Eq. (13), the expected value can be approximated with an independently and identically distributed (i.i.d.) random sample. This technique is called the "sample-path optimization" [23] or "sample average approximation" [26]. Thus, Eq. (14) is an estimator of the expected value of Eq. (13).

$$\hat{e} = \frac{1}{N}\sum_{j=1}^{N} F\left(\mathbf{\Delta}, \mathbf{UP^j}\right) \tag{14}$$

As aforementioned, the set of values $UP^1, ..., UP^N$, is an i.i.d. random sample of N realizations of the stochastic vector parameter $\mathbf{UP}$. The optimization problem obtained when Eq. (14) is used instead of Eq. (13), is the sample average approximation optimization problem (hereafter SAA) and can be solved deterministically with commercial solvers. Clearly, the solution of the SAA problem depends on the realizations $\mathbf{UP}$ that are included in the random sample. Moreover, the larger the size of the sample (N), the smaller is the difference between Eq. (13) and its estimator Eq. (14). Particularly when $N \to \infty$, $\hat{e} \to e$ [14].

Different samples of size N (i.e., different set of realizations of the stochastic vector parameter $\mathbf{UP}$) will shape different forms of Eq. (14). Therefore, the algorithms based on sample average solve the SAA problem several times with different samples [14, 27] and then select the most promising solution according to some predefined criteria as the final solution.

In this article the procedure proposed in Norkin et al. [21] and implemented in Verweij et al. [27] is applied. This is described as follows. Let $\hat{e}_N^1, \hat{e}_N^2, ..., \hat{e}_N^M$ be the values of Eq. (14) when solving M SAA problems, each one with a different sample of size N. Moreover, considered that $\hat{s}_N^1, \hat{s}_N^2, ..., \hat{s}_N^M$ are the solution (values of decision values) obtained when each of the aforementioned M SAA problems. An intuitive criteria for selecting the best solution among the M possibilities, would be to pick the solution with the best $\hat{e}_N$ value. A more sophisticated idea is to build an independent sample of size N', with $N' >> N$, and evaluate the solutions using this sample. Then, select the solution with the best value as it is expressed in Eq. (15) for a maximization problem.

$$\hat{s}_N^* \in \arg\max\{\hat{e}_{N'}(\hat{s}_N) : \hat{s}_N \in \hat{s}_N^1, \hat{s}_N^2, ..., \hat{s}_N^M\} \tag{15}$$

This idea takes advantage from the fact that even though using the large sample size N' for the optimization phase can be very time consuming (specially in NP-hard problems as the one addressed in this paper), using it for just for evaluation of the objective function Eq. (14) can be achievable in reasonable computing time [14].

5 Computational Experiments

This section describes the instances and methodology used for the evaluation of the proposed approach, and reports quantitative and qualitative results.

5.1 Problem instances

The instances construction is based on information from the REDD dataset [15]. As performed in Colacurcio et al. [7], instances with different sizes were considered. One of the key parameters to estimate was the users preferences. For estimating this parameter, information about the power consumption of the selected appliances on each household was analyzed. This involved cleaning the data from comparatively very small power consumption which are related to stand-by consumption of each appliance, for example, small screen leds. After this, for each combination of user and appliance, a probability of usage for each time slot was estimated (p_{lt}^u). With this probability, M instances were constructed for each sample size N as is described in Section 5.2. Additionally, from REDD dataset the mean power consumption of each appliance in KW (P_l^u) and the duration of the average time of utilization of each appliance (D_l^u) were estimated. When performing this noticeable differences were identified during the weekend, a behaviour that is usual for household users [8]. Therefore the instances were classified in weekdays and weekends.

Parameters E^u (maximum electric power contracted for each household) and C_t were obtained from the website of the Electric Company of Montevideo, Uruguay (`https://portal.ute.com.uy/`). Two instances size were considering, each one with two variations: weekdays (wd) and weekend (we):

– small ($s.wd$ and $s.we$). It has one household with seven deferrable appliances.
– large ($l.wd$ and $l.we$). It has two households with six and seven deferrable appliances respectively.

In the instances that corresponds to the small size Eq. (7) is not used since there is only one household and, thus, Eqs. (5) and (6) are enough for limiting the maximum consumed energy.

5.2 Experiment design

After some preliminary experimentation, the following sample sizes were chosen $N = 50{,}200{,}500$, 1000, 2000, 3000 and 10000. Within each sample size, the number of independent samples (M) was set to 100. The evaluation sample size (N') was set to 100000. The estimation of the ideal and nadir value for the weighted sum function were estimated with the procedure introduced in Section 4.1. This is performed within each N value. Additionally, five different weights configurations are used for exploring different trade-off between energy cost and user satisfaction (w_f,w_g): (0.99,0.01), (0.25, 0.75), (0.5, 0.5), (0.75, 0.25) and (0.01, 0.99). The SAA problems were solved with Gurobi [9] through Pyomo as modelling language [11].

Algorithm 1 Schema of a the Simulation-optimization (SO) approach.

initialize $SO(p^u_{lt}, N, M, \alpha, \beta)$
initialize list S of size M
for $m \leftarrow 0, m++, m \leq M$ **do**
  for $n \leftarrow 0, n++, n \leq N$ **do**
    for all $u \in U$ **do**
      for all $l \in L^u$ **do**
        for all $t \in T$ **do**
          initialize $t \leftarrow random(0,1)$
          if $t \leq p^u_{lt}$ **then** $UP^u_{lt} = 1$
          else $UP^u_{lt} = 0$
          end if
        end for
      end for
    end for
  end for
  $S[m] \leftarrow$ **Solve MDR**$(\alpha, \beta, \mathbf{UP}))$
end for
return S

5.3 Experimental results

The experimental results are reported in Tables 1-2, for the small and large instances considering weekday and weekend usage conditions, respectively. These Tables report for each instance, sample size (N) and weight vector values the following results: the mean and standard deviation of the runtime, the user satisfaction function F evaluated over N', the mean and standard deviation of the cost function G evaluated over N' (for the M different runs), and the values of F and G of the best compromising solution, i.e., the solution that has the minimal value of function H (Eq. (12)). It should be highlighted that since the cost function G (Eq. (2)) is deterministic, it is not affected by the sample size after the optimization process. In other words, for evaluation purposes: $G^N = G^{N'}$.

All the solutions of the SAA problems were solved to optimality since Gurobi was able to find solutions with 0% MIPGap for the compact mathematical formulation presented in Section 3 in relatively short computing times. The different combinations of weights were able to effectively explore the trade-off of the problem. Something interesting is that schedules that are biased towards minimizing the cost objective (with higher values of β) are more difficult to solve for Gurobi (computing times are as much of three times higher).

As expected, in general the larger the sample size N the higher the average the user satisfaction function value, since the expected value is better approximated by Eq. (14). Additionally, another important feature is that increasing sample size N led to a remarkable reduction of the variability of the results (measured through the standard deviation). Fig. 1 exemplifies this behavior, reporting the average and standard deviation of function F for the M independent samples for the three combinations with larger α, i.e., in which F has preponderance over the cost, in the large instance for the weekday patron.

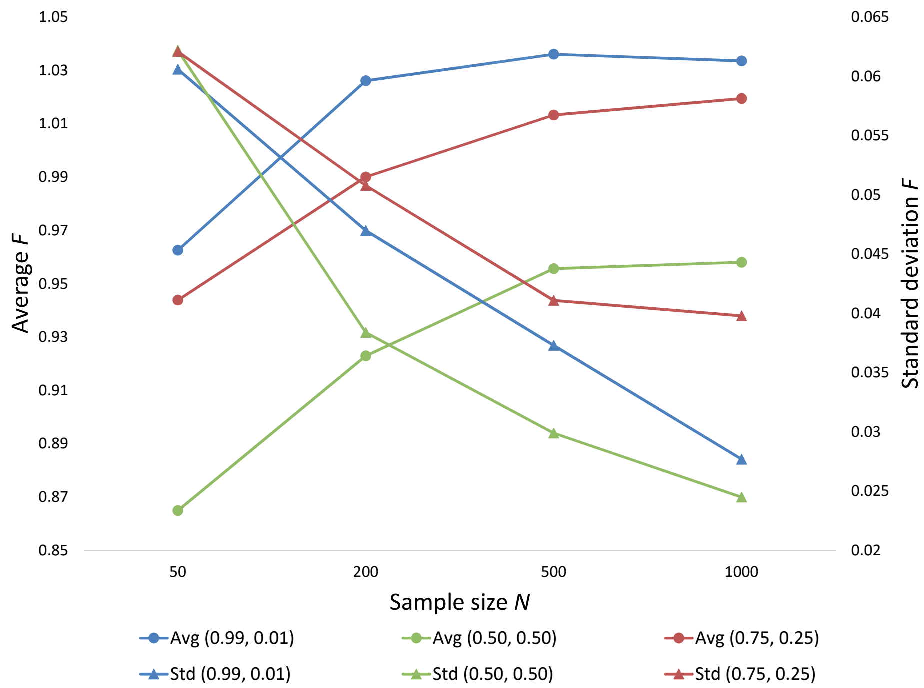

Fig. 1: Sensitivity analysis of average and standard deviation of F in l.wd instance.

Table 1: Results of small instance.

N	(α,β)	Time(sec)		$F^{N'}$		$G^{N'}$		$F(H_{best}^{N'})$	$G(H_{best}^{N'})$
		Avg	Std	Avg	Std	Avg	Std		
				Small instance weekday (s.wd)					
50	(0.99,0.01)	0.04	0.07	0.5065	0.0405	115.91	8.65	0.5761	103.73
	(0.01,0.99)	0.13	0.09	0.2245	0.0192	89.39	0.00	0.2468	89.39
	(0.50,0.50)	0.08	0.08	0.4128	0.0464	96.84	2.36	0.4592	93.37
	(0.75,0.25)	0.05	0.07	0.4849	0.0476	103.63	4.40	0.5062	98.75
	(0.25,0.75)	0.11	0.08	0.3104	0.0478	90.99	0.95	0.2455	89.39
200	(0.99,0.01)	0.05	0.09	0.5445	0.0302	115.10	6.94	0.5877	104.83
	(0.01,0.99)	0.13	0.09	0.2342	0.0151	89.39	0.00	0.2462	89.39
	(0.50,0.50)	0.09	0.07	0.4270	0.0401	94.38	2.05	0.4608	93.37
	(0.75,0.25)	0.08	0.11	0.4835	0.0400	99.14	1.58	0.5170	98.20
	(0.25,0.75)	0.14	0.12	0.3036	0.0355	90.50	0.37	0.3048	89.74
500	(0.99,0.01)	0.06	0.11	0.5590	0.0251	113.08	2.86	0.5869	104.84
	(0.01,0.99)	0.14	0.10	0.2404	0.0088	89.39	0.00	0.2463	89.39
	(0.50,0.50)	0.11	0.11	0.4854	0.0266	98.07	0.72	0.4503	93.37
	(0.75,0.25)	0.10	0.13	0.5138	0.0432	100.75	2.82	0.5866	102.63
	(0.25,0.75)	0.14	0.13	0.3380	0.0301	90.86	0.44	0.3034	89.95
1000	(0.99,0.01)	0.02	0.01	0.5699	0.0229	112.93	1.11	0.5318	104.28
	(0.01,0.99)	0.10	0.01	0.2419	0.0073	89.39	0.00	0.2497	89.39
	(0.50,0.50)	0.07	0.01	0.5016	0.0235	98.15	0.50	0.4353	93.37
	(0.75,0.25)	0.05	0.07	0.5192	0.0324	99.54	2.00	0.5150	98.20
	(0.25,0.75)	0.09	0.01	0.3402	0.0236	90.80	0.12	0.3432	90.57
				Small instance weekend (s.we)					
50	(0.99,0.01)	0.03	0.08	0.5271	0.0446	41.49	11.05	0.6095	29.66
	(0.01,0.99)	0.05	0.08	0.2725	0.0305	23.18	0.00	0.3160	23.18
	(0.50,0.50)	0.05	0.09	0.4864	0.0448	26.53	1.69	0.5298	25.41
	(0.75,0.25)	0.02	0.01	0.5348	0.0349	30.88	3.60	0.6003	28.81
	(0.25,0.75)	0.03	0.01	0.4163	0.0499	24.36	0.65	0.3334	22.05
200	(0.99,0.01)	0.03	0.08	0.5748	0.0358	38.37	9.51	0.5907	28.81
	(0.01,0.99)	0.05	0.09	0.2955	0.0152	23.18	0.00	0.3157	23.18
	(0.50,0.50)	0.08	0.12	0.4842	0.0280	25.08	0.48	0.5412	25.41
	(0.75,0.25)	0.04	0.08	0.5612	0.0242	28.95	0.88	0.5984	28.81
	(0.25,0.75)	0.08	0.11	0.3976	0.0346	23.67	0.28	0.3013	21.76
500	(0.99,0.01)	0.04	0.08	0.6048	0.0234	37.03	3.77	0.6005	28.81
	(0.01,0.99)	0.08	0.13	0.3011	0.0053	23.18	0.00	0.3157	23.18
	(0.50,0.50)	0.09	0.14	0.4783	0.0203	24.73	0.19	0.4809	23.33
	(0.75,0.25)	0.04	0.09	0.5611	0.0275	28.22	1.18	0.5316	25.41
	(0.25,0.75)	0.07	0.10	0.3174	0.0300	23.23	0.14	0.2948	22.76
1000	(0.99,0.01)	0.01	0.00	0.6176	0.0155	36.92	2.03	0.5901	28.82
	(0.01,0.99)	0.03	0.00	0.3027	0.0024	23.18	0.00	0.3054	23.18
	(0.50,0.50)	0.03	0.00	0.5467	0.0368	26.94	1.78	0.5321	25.41
	(0.75,0.25)	0.02	0.03	0.5845	0.0092	28.89	0.11	0.6084	28.81
	(0.25,0.75)	0.04	0.00	0.4665	0.0298	24.38	0.48	0.4355	23.76

Table 2: Results of large instance.

N	(α, β)	Time(sec)		$F^{N'}$		$G^{N'}$		$F(H_{best}^{N'})$	$G(H_{best}^{N'})$
		Avg	Std	Avg	Std	Avg	Std		
Large instance weekday (l.wd)									
50	(0.99,0.01)	0.07	0.07	0.9626	0.0606	200.60	15.23	1.0071	170.06
	(0.01,0.99)	0.40	0.15	0.3721	0.0350	131.41	0.00	0.4312	131.41
	(0.50,0.50)	0.21	0.10	0.8650	0.0622	144.47	2.86	0.7668	136.91
	(0.75,0.25)	0.19	0.15	0.9439	0.0621	160.94	9.52	1.0695	151.33
	(0.25,0.75)	0.24	0.08	0.7078	0.0886	135.99	1.62	0.6876	133.36
200	(0.99,0.01)	0.09	0.12	1.0262	0.0470	197.83	11.94	0.9115	165.68
	(0.01,0.99)	0.33	0.11	0.3890	0.0295	131.41	0.00	0.4322	131.41
	(0.50,0.50)	0.19	0.09	0.9230	0.0384	144.78	1.39	0.9230	140.15
	(0.75,0.25)	0.17	0.11	0.9901	0.0508	152.26	5.89	1.0213	145.69
	(0.25,0.75)	0.28	0.10	0.7248	0.0428	134.90	0.81	0.7450	134.03
500	(0.99,0.01)	0.08	0.12	1.0361	0.0373	195.71	8.13	1.0370	180.96
	(0.01,0.99)	0.31	0.09	0.3883	0.0277	131.41	0.00	0.4332	131.41
	(0.50,0.50)	0.22	0.14	0.9557	0.0299	145.26	0.33	1.0302	145.69
	(0.75,0.25)	0.16	0.11	1.0133	0.0411	151.98	5.51	1.0880	150.11
	(0.25,0.75)	0.29	0.12	0.7860	0.0441	136.49	1.26	0.7368	134.19
1000	(0.99,0.01)	0.08	0.07	1.0336	0.0277	195.49	8.24	1.0852	191.66
	(0.01,0.99)	0.32	0.08	0.3892	0.0263	131.41	0.00	0.4281	131.41
	(0.50,0.50)	0.19	0.08	0.9581	0.0245	145.21	0.22	0.9714	144.67
	(0.75,0.25)	0.13	0.05	1.0195	0.0398	151.37	5.50	1.0582	149.76
	(0.25,0.75)	0.27	0.09	0.7879	0.0364	136.46	0.96	0.7436	134.62
Large instance weekend (l.wd)									
50	(0.99,0.01)	0.10	0.13	1.0007	0.0620	287.69	13.86	1.1515	277.16
	(0.01,0.99)	0.33	0.12	0.4020	0.0190	197.55	0.16	0.3935	195.93
	(0.50,0.50)	0.17	0.12	0.8944	0.0620	209.69	2.72	0.9664	207.08
	(0.75,0.25)	0.15	0.11	0.9592	0.0693	222.08	9.62	1.0140	211.18
	(0.25,0.75)	0.22	0.12	0.7009	0.0834	201.07	1.49	0.6986	199.33
200	(0.99,0.01)	0.07	0.10	1.0614	0.0417	280.86	7.46	1.1160	271.33
	(0.01,0.99)	0.32	0.13	0.4091	0.0174	197.57	0.00	0.4347	197.57
	(0.50,0.50)	0.15	0.11	0.9796	0.0470	212.28	0.98	1.0626	211.73
	(0.75,0.25)	0.15	0.11	1.0018	0.0458	251.5656	13.567	1.1007	216.66
	(0.25,0.75)	0.22	0.13	0.8277	0.0563	204.74	1.33	0.7558	200.77
500	(0.99,0.01)	0.10	0.12	1.0944	0.0333	278.59	3.21	1.1403	268.53
	(0.01,0.99)	0.32	0.10	0.4139	0.0152	197.57	0.00	0.4345	197.57
	(0.50,0.50)	0.17	0.12	1.0065	0.0356	211.98	0.43	1.0541	211.73
	(0.75,0.25)	0.16	0.11	1.0171	0.0419	249.10	11.78	1.1226	216.16
	(0.25,0.75)	0.21	0.11	0.8301	0.0464	204.57	1.25	0.8179	202.28
1000	(0.99,0.01)	0.05	0.00	1.1060	0.0279	278.80	2.26	1.1365	271.58
	(0.01,0.99)	0.29	0.01	0.4129	0.0136	197.57	0.00	0.4319	197.57
	(0.50,0.50)	0.12	0.01	1.0155	0.0289	211.84	0.23	1.0491	211.73
	(0.75,0.25)	0.11	0.01	1.0347	0.0365	251.14	7.83	1.1169	216.16
	(0.25,0.75)	0.18	0.03	0.8362	0.0330	204.48	1.21	0.8124	202.19

6 Conclusions

This article studied the household energy planning problem, a relevant optimization problem that arises in the context of modern smart cities.

A novel bi-objective mathematical formulation of the problem was presented, accounting for uncertainty in the preferences of using each appliance. In this formulation, the aim is to schedule on a daily basis the usage of deferrable appliances while optimizing two conflicting objectives: the cost of the electricity–based on time-of-use tariff–and the users satisfaction. The users satisfaction is estimated through historical data of when (which part of the day) users prefer to use each appliance. However, since there is considerable variation of these preferences, a stochastic resolution approach was used to include the randomness of this parameter. The proposed problem was solved using the Sample Average Approximation method, which is a simulation-optimization approach that combines Monte Carlo simulation and deterministic mixed integer programming. Different real-world instances were considered and solved with different parametric combinations. The approach was able to propose different solutions that explore the trade-off between the two criteria in reasonable computing times. Particularly, for larger values of sample size the standard deviation of the results given by the method was significantly reduced.

Additionally, the initial tests performed in this work were execute in relatively small computing times even for the large instance. This shows the validity of the proposed integer mathematical formulation and the simulation-optimization approach as useful tools to perform practical load scheduling in smart homes. However, for enhancing performance of the model in a particular household, it is important to first gather specific data of that household to accurately estimate the key parameters of the model, such as the stochastic user preferences.

For future work, a crucial research line is to expand the computational experimentation. This should include using larger sample sizes and number of independent samples within each size (M) for exploring whether the accuracy of the solutions can be enhanced. Also, to study the competitiveness of the approach for larger instances in which buildings with more than two households are considered. Another way the instances can be enlarged is to include other kinds of appliances, such as non-deferrable loads, and renewable power generators within the household, e.g., solar or wind power generators.

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Seleção de um Sistema de Gerenciamento de Transportes numa Empresa do Setor Educacional

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Resumo. O uso da Tecnologia da Informação (TI) tem sido fator-chave para que empresas alcancem um nível de serviço adequado às expectativas de seus clientes, gerando um processo mais ágil e enxuto. Este artigo abordou as fragilidades nos processos de uma empresa do setor educacional cuja área de Logística ainda não emprega um sistema informatizado que auxilie no planejamento, na programação, no controle e na execução do transporte. Para tanto, analisou-se, com base em orientações técnico-teóricas relacionadas à TI e com suporte do método de tomada de decisão multicritério *Analytic Hierarchy Process* (AHP) acoplado ao modelo Benefícios, Oportunidades, Custos e Riscos (BOCR), a melhor alternativa para a seleção de um *software Transportation Management System* (TMS) considerando a realidade da empresa. A avaliação das alternativas s*oftware* próprio e *software* de mercado, foram efetuadas por uma equipe de especialistas. O resultado indicou *software* de mercado como a melhor alternativa, obteve a maior prioridade global, destacando-se como a melhor solução.

Palavras-chave: Sistema de Gerenciamento de Transportes, Fatores Críticos de Sucesso, Modelo AHP-BOCR, Empresa do Setor Educacional.

1 Introdução

O suporte de Tecnologia da Informação (TI) aplicado a diversos processos é o que tem garantido a organizações crescimento e visibilidade em um mercado cada vez mais competitivo. Assim, empresas que não lançam mão de tal suporte têm perdido oportunidades de negócio e de crescimento. De acordo com [1], as empresas devem investir em tecnologia e inovação para garantir a sua sobrevivência.

A melhoria da qualidade do serviço logístico – alcançada pela aplicação da TI – leva a maior satisfação do cliente e, desse modo, aumenta suas chances de fidelidade à empresa [2]. Considerando, portanto, que o resultado da aplicação das Tecnologias da Informação nos processos empresariais significa uma gestão mais eficaz e veloz na administração de recursos humanos e de equipamentos, é compreensível que as empresas busquem, constantemente, atualização tecnológica. Pois, como bem pontuam [3], o