Customized transition towards smart homes: A fast framework for economic analyses

Michael David de Souza Dutra[a,*], Gerson da Conceição Júnior[a], William de Paula Ferreira[a], Matheus Roberto Campos Chaves[b]

[a] *École Polytechnique de Montréal, C.P. 6079, Succursale Centre-Ville, Montréal, QC H3C 3A7, Canada*
[b] *Faculdade Cidade Verde*

Abstract

Smart homes allow the optimization of energy usage so that households can reduce electricity bills, or even make profits. By 2020, 20% of all households in Europe and 35% in North America will be expected to become smart homes. Although smart homes seem to be the future for homes, many customers have the perception that a transition from current homes to smart ones is not worth the price. Adopting a smart home concept requires a significant amount of investments for which the households desire a positive return. A question in this context is the following: for a given household, when and/or what set of home appliances/technologies should be acquired so that the investment made by householder has a positive financial return? The available tool to answer that question can be time-consuming from a practical perspective. Based on our previous work, this paper proposes a framework to help the transition from current houses to smart homes considering customized electricity usage and economic measures, including the net present value (NPV) one. A tree algorithm is developed to decrease the time needed by an economic analysis of each possible acquisition combination of smart appliances or equipment for a given user. The proposed framework is tested on 40 cases covering all Brazilian capital cities, whose results are available online and may be used directly as an approximation for economic analyses. An example of one case is described in details for implementation purposes. Results show that the proposed tree algorithm is able to reduce days of CPU time to solve the problem and NPV should be used as an economic measure to answer the aforementioned question.

Keywords: Smart Home, Economic Analysis, Energy Management System, Interior Point.

1. Introduction

The number of smart homes is expected to increase considerably with the progress of smart grids worldwide and the usage of demand response programs in the residential sector by many distribution companies [1, 2].

Governments encourage this trend due to at least two reasons. Firstly, the distributed generation by smart homes permit to postpone investments in the grid infrastructure. Second, local renewable generation reduces the environmental impact. Smart home owners could be interested in making profits or reducing their electricity bill and to keep a pleasant level of comfort, which can be done by scheduling the work-time of appliances [3].

According to [4], an important smart home barrier is the consumer perception that technology adoption towards smart homes is not worth the price. Given that the investment to transform homes in smart homes is representative, householders need to know the profitability of the investment in that transition to decrease investment risks. One way to invest is by the acquisition of smart-home components (SHCs), which is defined to be the technologies, machines, and appliances available for smart homes, such as wind turbines (WTs), photovoltaic panels (PVs), energy storage systems (ESSs), combined heating and power (CHP), electric vehicles (EVs), heating, ventilation, and air-conditioning (HVAC), water heaters (WHs), solar collectors (SCs), electric shower, internal combustion engine (ICE), fridge, freezer and appliances. As mentioned in [5], *"... the consideration of either net present values or discounted payback periods are the most useful approaches as these consider the future value of money"*. In this paper, the net present value (NPV) is used to consider the future value of money for a customized transition towards smart homes.

A challenge for householders who want to transform their home in smart homes is the absence of fast tools for an economic analysis to choose the best combination of SHC to be acquired. Suppose that the householder h is able to acquire any SHC of the following set: $\{\mathrm{SHC}_1,$

*Corresponding author
Email addresses: `michaeldavid.dutra@polymtl.ca` (Michael David de Souza Dutra), `gjunior@thinkmax.com` (Gerson da Conceição Júnior), `william.ferreira@polymtl.ca` (William de Paula Ferreira), `chaves.matheus@hotmail.com.br` (Matheus Roberto Campos Chaves)
URL: `https://michaeldavid.now.sh/` (Michael David de Souza Dutra)

$\mathrm{SHC}_2,\ldots,\mathrm{SHC}_{10}\}$. There is a total of 1024 combinations of SHC as option for investment: selecting one of them is not an easy task. An economic analysis is needed for each combination to determine which combination is the best one to maximize the NPV considering the specific data of householder h: its house structure, the weather in his city, the prices from its utility company, its consumption, etc.

In addition to the high number of system combinations, it is important to use realistic models to represent each SHC [3]. More representative models imply high complexity. Hence, few papers have considered optimization for an economic analysis of SHC acquisition for a specific user and simulation is more frequently used. Even though simulation is more accurate, it may be time-consuming for an economic analysis of each possible SHC acquisition combination. To the best of our knowledge, only the work of Dutra *et al* [6] proposes a framework to address the high number of system combinations and the representativity of SHC models, but the framework is time-consuming: for 1024 combinations and using "yearly savings approach", the CPU time to solve this example is more than one month.

This paper proposes a framework to determine the best combination of SHC in accordance with NPV measure to be acquired for a specific user. The framework uses SHC models from [3], which were considered representative given their performance in relation to reality. Using a tree-structure to store optimization problems and Interior Point algorithm with warm initial solutions, the proposed framework is around 44% faster compared with the recent approach in [6].

The proposed framework is tested on 40 case studies covering all Brazilian capital cities. One case study is detailed in this paper, but the complete set of results is available online[1]. Many Brazilian householders do not have automated sensors to obtain the input data for the framework, so the online results may be used as an initial economic analysis. However, if the householder can collect its own data, the results with a personalized implementation of the framework will be better, since that an economic analysis depends on the application. Advises are provided for householders regarding the usage of specific algorithms in the framework implementation.

The remaining of this paper is organized as follows. Related Works is given in Section 2. An economic analysis should consider not only the user cost, but also the user comfort level, which means that a trade-off between cost and discomfort level as performance criteria is needed. Hence, in Section 3, multi-objective optimization (MOO) is reviewed. Recent papers that used multiobjective optimization in the context of smart houses are also reviewed. Section 4 presents the proposed framework, its optimization models and strategies. Section 5 provides computational results. Finally, conclusions are provided in Section 6.

[1] www.michaeldavidsd.com

2. Related Work

The majority of the literature related economic analysis of smart homes has focused on a few combinations of SHCs [6]. This section provides a literature review of recent works on the topic.

In the context of European countries, Gur et al. [7] found that neither new nor reused batteries make PV-batteries systems profitable, but each country has its specific reasons.

Considering the Switzerland, Schopfer et al. [8] present that photovoltaic battery systems are not profitable due to the high cost of batteries, but PV-only systems may be profitable. Considering 4190 households load profiles, results show that there is high variability in the optimal system configuration and in the profitability due to the household's individual specificities, even for consumers with similar total annual demand.

The work in [9] proposes a techno-economic analysis of a shared energy storage and household batteries for residential consumers with smart appliances. Using PV generation and real demand data from 39 households in Netherlands, the authors computed the payback period and the levelized costs of energy for the aforementioned ESS systems. A mixed integer linear problem (MILP) minimizes the energy acquisition cost from the grid. Users are able to inject electricity into the grid, but there is no reward for it. The horizon plan for the scheduling problem is one year. Results show economic unfeasibility for the systems, which have a payback ranging from 26 to 43 years.

Yu [10] presents a French case: considering the cost decline of Lithium-ion batteries and PVs, the household profitability of systems composed by these two SHCs and their massive integration in power systems are studied. The PV prices in the future were estimated by the experience curve method. A ratio measure, based on the NPV is used to determine the systems' economic feasibility. Electrical heating is ignored in the study. From end-users perspective, results show that Li-ion batteries with PVs system has a high probability to be profitable by 2030. From the grid perspective, a system of PVs without batteries has a bigger impact than a system composed of PVs with batteries since the latter needs less grid injection.

Chatzisideris et al. [11] investigate the environmental and economic gains of organic photovoltaic (OPV) for self-consumption combined with batteries in the context of the Greek and Danish residential sector. For both countries, the household average consumption of 4000kWh/year is taken as input for a six-step framework in which there is a simulation method. Considering a 20-year lifetime project and 100 combinations of system sizes (OPV and battery with a discrete size between, respectively, 1-10kWp and 1-10 kWh), results show that an OPV-only system with 1kWp gives the best option for both countries, with a NPV of 1216€ for Denmark and a NPV of 1164€ for Greece. Considering an OPV price reduction, OPV-battery systems are more profitable than OPV-only systems when

OPV cost is at most 0.9€/Wp and 1.6€/Wp, respectively, for Denmark and Greece.

Bai et al. [12] present an economic analysis of second-life electric vehicle batteries combined with PVs for many provinces in China considering residential, commercial and industrial sectors. NPV is computed considering a 30-year lifetime project. Each province has its own specificities such as the implementation of a TOU and retail electricity prices. Two strategies for the usage of batteries are considered: the first to increase self-consumption rate (SCR) from PV production, and the second to increase SCR and also load leveling. Householders from a few Chinese regions are able to make profits only with the second strategy. Focusing on PV-only, its implementation will benefit all sectors from every province considering the government subsidy. Without subsidy, only 61% of the regions have a positive NPV for the residential sector considering a SCR of 40%.

Using real data for PV production and electricity consumption, which was collected for one year in a UK home, Uddin et al. [13] studied the economic viability of batteries and PVs. They develop a detailed and reliable battery degradation model. It is assumed that near the 5^{th} year the battery will have an important efficiency loss, so the annual electricity usage and generation are set the same over five years. The time dimension is only used in the battery degradation model. The economic evaluation is made through the annual savings, i.e. the sum of revenue minus the expenses for one year. Results show that without considering the cost of battery degradation, the system PV-4kW and the system of PV-4kWh combined with a battery-2kWh have an annual savings of £185 and £193, respectively. However, considering the degradation cost, the battery makes the project unprofitable.

In the Czech Republic context where there is small Feed-in-Tariff (FIT), Kichou et al. [14] propose two simulation models (one for summer and one for winter) to find the optimal solution between performance and financial cost for systems composed by PVs, CHPs and batteries for a research building. Performance is directly proportional to a ratio of energy bought from the grid over self-consumption. The financial cost is measured by NPV and discounted payback period. Yearly savings approach is used. Results show that the existing system in the building has a payback of 28.7 years, which is bigger than the project lifetime: 25 years. However, increasing the PV capacity by 24.2kWp and using the control strategies given as output by the simulation, the payback decreases to 9.7 years with an NPV of 35,491€. It is worth to mention that the control strategies are the main driver of economic improvements.

Akter*et al* [5] propose a framework that gives economic measures to assess a battery system with PVs considering an Australian study case. Results show that NPV and payback of a system with only PVs are better than systems with PVs and batteries. PVs are economically acceptable in on-grid systems, but not profitable in off-grid systems due to the excess of energy, after a threshold of installed capacity. Akter*et al* [5] consider reduction in CO_2 emissions and options between different tariffs. As methodology, economic evaluations are conducted by considering a project with a life-time of 25 years for different scenarios using their own simulation.

Later, Say et al. [15] studied the profitability of 441 battery and PV-battery system combinations in Perth, Australia: PV and battery capacities range, respectively, from 0 to 10 kWp with a step-size of 0.5 kWp and from 0 to 20 kWh with a step-size of 1 kWh. The project lifetime was set to 10 years. The years of 2018 and 2013 were used as candidates for the project installation date. For both years, various combinations of PV-only and PV-battery systems have a positive NPV. Then, considering different rates of increasing electricity prices (RIEP), the NPV is calculated considering that projects starting in each year from 2018 to 2033. Yet, there are various combinations of profitable PV-only and PV-battery systems, but the results show that batteries should be avoided before 2020 and 2024 for an annual RIEP of 5% and 0%, respectively. A similar analysis is conducted for different FITs. These results answer the question: "*When should PV and/or ESS be installed to maximize profitability?*", which is also done in [6].

Few studies treated the profitability of SHC in South America. Focusing in PV systems, economic analysis are presented by Coria et al. [16] and by Espinoza et al. [17] for the Argentinian and Peruvian cases, respectively. There are many other studies focusing on the economic analysis of PV-only system and PV-batteries systems in different residential locations. Please, see [18] for a review summarizing many applications in various countries.

The economic benefits of other SHCs have also been studied by some recent works. A house design is studied by Xie *et al* [19]. Payback analysis for μ-CHP, phase changing materials, heat pumps, PVT, SC, and PVs systems, are described. The paper shows a payback period of 13, 11 and 6.5 years or more for μ-CHP,PVs/PVT and WH, respectively. Methodology: simulation with design software, SketchUp® by Trimble.

The integration of EV with PV in the Hawaii context is presented by Coffman el al. [20]. The total cost of ownership is computed for six EVs, five hybrid electric vehicles (HEV) and six internal combustion engine vehicle (ICEV). Results show that EVs are less attractive than ICEV or HEV if subsidies are not taken into account. If subsidies are considered, only one Nissan Leaf EV becomes more attractive than some HEV and ICEV. If PVs are considered besides EV, EVs become more favorable economically.

Mazzeo [21] investigates 100 systems composed by PVs, batteries and the Nissan Leaf as EV in a residential context. The capacity of PVs and batteries is determined to maximize the NPV in two independent ways: one constraining the energy amount bought from the grid (way I), another constraining the energy amount sent to the grid (way II). Daily home load profiles are used, but average values are considered through the lifetime of the battery and PV systems. Vehicle recharge is allowed only in nocturnal hours, between 10PM - 8AM. Comparing with ICEVs, results show that the residential system PV-ESS-EV has a positive NPV after a threshold of the distance traveled by the EV. The NPV ranges from near 0 to 72360€. Depending on the EV daily distances traveled, two sets of solutions are provided for the optimal battery and PV capacities: for the way I, battery and PV capacities range from 12 to 27kWh and from 6 to 10 kW, respectively; for the way II, the ESS capacity is 3kWh and the PV capacity ranges from 2 to 3kW.

Focusing on PV self-consumption, an optimization MILP model for the configuration and sizing of PV, batteries and heat pumps is presented by Beck et al. [22]. The total cost ownership is minimized. Water and space heating are modeled without technical constraints, only power flow is considered. Heat pumps and ESS have more details in their models. Three load profiles collected during the years of 2012 and 2012 from German homes and solar load profiles from the Stuttgart city are taken into account by the model. Combining two FITs and three electricity price scenarios, results show that the optimal rated power of heat pump, PV and electrical heater are hardly ever influenced by electricity price increase or by FITs. In all, six scenarios, the rated capacity for batteries are lower than 5kWh and the rated power of PV ranges from 0 to 10kW. Sensitivity analysis provides a deeper analysis of prices and user consumption. The authors conclude that PV and ESS sizing is mainly dependent on user demand.

The literature has focused on specific or isolated sets of SHC when the topic is economic analysis. In addition, the majority of papers has analyzed PVs and ESS profitability. Note that these results highlight the importance of considering the economic analysis for each specific system, even if systems have identical locations, which is explicitly mentioned in [23, 8, 6, 22]: the economic efficiency of SHCs depend on future prices, on regulatory laws and on user behavior. Most of the literature considers numerical analysis and simulation models for the profitability study of SHCs. Among works that use optimization models [23, 9, 6, 22, 21], to the best of our knowledge, only the work in [6] has proposed a framework for the problem of obtaining a payback analysis of each possible SHC acquisition combination for any household. The framework is based on optimization models and uses real data. The framework is able to answer the question: when and/or what SHCs should be acquired for a specific site to maximize profitability? In addition, the framework may be used for sizing of residential dwellings. However, the framework has scalability issues and the simple payback measure is not reliable for an economic analysis in the context of smart homes: both drawbacks are improved in this work. Compared with [6], our approach presents days of CPU time reduction.

Thus, house owners need a fast tool to assist them in a personalized decision about how to mitigate risks in the adoption or change towards a smart home, which is the motivation of this work. The main **contributions** of this work are: (i) the proposition of a holistic and fast framework that explores every SHC acquisition combination for any user considering and NPV as economic measure. The output tool determines the best investment in the transition from existing home to a smart house concept; (ii) the proposition of a tree algorithm combined with Interior Point algorithm to decrease the computational burden; (iii) the availability of a online compiled data-base for an approximated economic analysis for smart homes in 40 Brazilian cities.

3. Review of multiobjective optimization (MOO)

According to the reference [24], optimization problems involving several conflicting objectives are often grouped together to have a mono-objective formulation using, for example, a weighted sum approach. However, the work in [25] shows that instead of a single and optimal solution, the presence of multiple objectives gives rise to a set of optimal solutions that are not dominated, or also, according to [26], effective solutions. This discussion is situated in the multiobjective optimization field, which is rapidly reviewed in this section. For surveys in MOO, we invite the reader to see [27] and [28]. An ample and more detailed discussion is available in [29].

3.1. Definitions

Suppose $C \in R^{k \times n} : Cx = [f_1(x), ..., f_k(x)]^T$ and $X = \{x \in R^n : Ax = b, x \geq 0\}$, where $A \in R^{m \times n}$ and $b \in R^m$. According to [30], the problem $\min_{x \in X} f_1(x), ..., f_k(x)$ finds all efficients solutions, which are defined as following: x^0 is said to be an *Efficient solution* or *Pareto optimal* if $x^0 \in X$ and there exists no $x^1 \neq x^0 \in X$: a) $f_i(x^1) \leq f_i(x^0)\ \forall\ i \in \{1..k\}$, and b) $f_j(x^1) < f_j(x^0)$ for some $j \in \{1..k\}$. A feasible solution x^0 is *Weakly Pareto optimal* or *Weakly efficient solution* if there exists no feasible solution $x^1 \neq x^0 \in X : f_i(x^1) < f_i(x^0)\ \forall\ i \in \{1..k\}$. Given a (respectively weakly) efficient solution x, the point $(f_1(x), ..., f_k(x))$ is called a (respectively weakly) efficient point.

Suppose $F(x) = [f_1(x), ..., f_k(x)]^T$. So, similar definition is used for domination in [31]: *"The vector $F(\hat{x})$ is said to dominate another vector $F(x_p)$, denoted $F(\hat{x}) \prec F(x_p)$, if and only if $f_i(\hat{x}) \leq f_i(x_p)$ for all $i \in \{1, 2, ..., k\}$ and $f_j(\hat{x}) < f_j(x_p)$ for some $j \in \{1, 2, .., k\}$. A point $x^* \in X$[2] is said to be globally pareto optimal or a globally efficient point for multi-criteria optimization problem if and only if there does not exist $x \in X$ satisfying $F(x) \prec F(x^*)$. $F(x^*)$ is then called globally nondominated or noninferior."*

Another definition given in [30], generalized here, is for supported and unsupported efficient points. An efficient

[2] In the original paper is "C"

point $(a, b, ..., k)$ is supported if exists scalars $\lambda_i \in \{1..k\}$: $\sum_k \lambda_k = 1$ and a feasible solution x such that x minimizes $\sum_k \lambda_k f_k(x)$ and $f_1(x) = a, f_2(x) = b, ..., f_k(x) = k$. The paper [32] corroborates that definition informing that supported points are located in convex regions of the objective space: *"Non-supported solutions can only be found coincidently when they are discovered as intermediate solutions on the way towards a supported solution."*

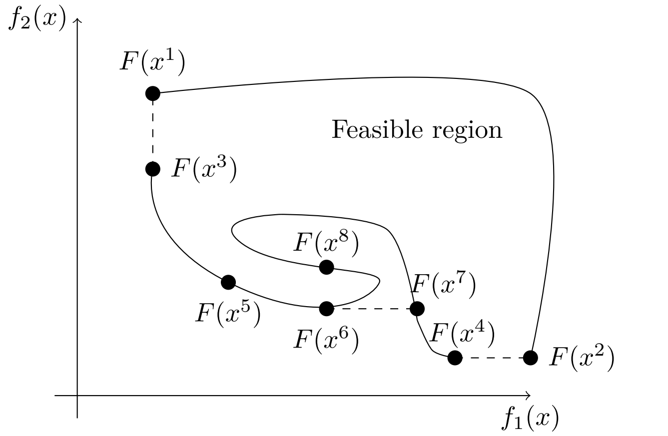

Figure 1: Example of definitions in a bi-objective feasible region.

To exemplify these definitions above, Figure 1 shows an objective space with their feasible region and some feasible points. The solution x^1 is a weakly efficient solution because there is no other solution $x^k \in X : x^1 \neq x^k$ and $f_i(x^k) < f_i(x^1)\ \forall\ i\{1, 2\}$. Besides that, x^1 is not an efficient solution because $x^3 \in X : f_1(x^3) \leq f_1(x^1)$ and $f_2(x^3) < f_2(x^1)$. The solutions x^2 and x^7 are also only weakly efficient points by similar analysis with, respectively, solutions x^4 and x^6. The solutions x^4,x^5 and x^6 are efficient solutions. Finally, the solution x^8 give a point F(x^8) that is dominated by F(x^5) for instance. Moreover, F(x^8) is not a supported point since it is not located in a convex region of the objective space. In this case, F(x^8) is not interesting to be found, however there are cases where unsupported points are valuable since they are efficient points, as F(x^9) in Figure 2.

To find efficient solutions that are in the extreme region of the Pareto Front (PF), for instance, solutions x^3 and x^4 in Figure 1, one can use Lexicographic Optimization explained at [33, section 3.1].

3.2. Approximated Pareto Front (APF)

It is known that weighted sum method finds all supported efficient solutions, but it cannot find unsupported efficient points [27]. This drawback can be avoided by ϵ-constraint [32, Algorithm 1] or Normal-Boundary Intersection (NBI) [31] methods.

The ϵ-constraint method, is well known in the literature. Only one function is kept as the objective, and the other goal functions are set as constraints. The right

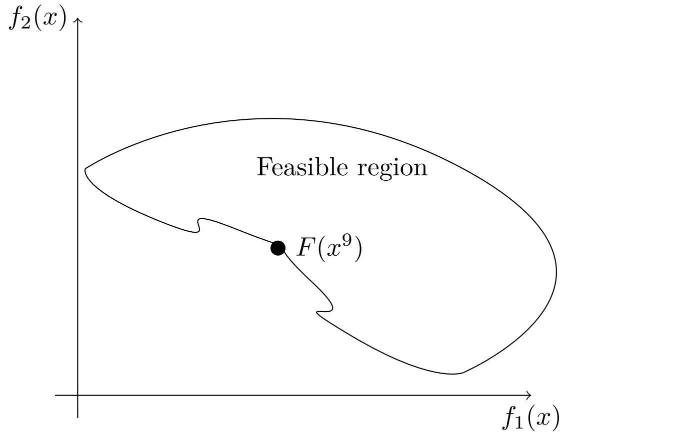

Figure 2: Example of an unsupported and efficient point.

side of each these constraints j will be ϵ_j values. One need to change monotonically these ϵ_j values by a constant δ_j. According to [30], the method can generate every efficient point for a bi-objective case. Supporting this argument, [34] says that ϵ-constraint method *"is capable of generating any non-dominated point with appropriate choices of parameters."* For [35], the method is probably the best because it is able to generate all pareto optimal points varying $\epsilon_j > 0$ values.

Another advantage of the ϵ-constraint method is that it can find unsupported efficient solutions, in other words, the method finds solutions independently of convexity or non-convexity of the objective functions; and there is no need to scale the objective functions to a common scale before applying the method [33, 35]. Generalization for that method is also done, for instance, [32] generalizes the ϵ-constraint method for the case with a high number of objectives for discrete multiobjective optimization problems using an adaptive ϵ-constraint method. This new method solves a series of instances from an auxiliary problem, optimizing one of the objectives, while the remain objectives are set as constraints.

The ϵ-constraint method has a drawback due to the need to choose values for δ_j. As said by [32]: *"Since only one solution can be found in each interval, the discretization has to be fine enough not to "miss" any Pareto-optimal solution. In the worst case, the difference between objective vectors might be as small as the machine accuracy of the computer used to run the algorithm."* In practice, instead of enumerating all efficient points, a subset of them is found to represent an APF, which can be done with [32, Algorithm 1], for instance.

The second method, NBI method from [31], is an approach that produces an even spread efficient points distribution. The method can be summarized by Algorithm 1 considering that optimization problem: $\min_{x \in \mathbb{R}^n \cap X} F(x) = [f_1(x), f_2(x), \ldots, f_k(x)]^T$.

The Algorithm 1 has three parts. The first one, represented in lines 1-5, is done to find the Ideal Point. That point is formed by the composition of the individual local

Algorithm 1 - NBI method

1: Find Utopia Point (Ideal Point) F^*:
2: **for all** $i \in \{1, \dots, k\}$ **do**
3: finds $x_i^* : f_i^* = \min\limits_{x \in \mathbb{R}^n \cap X} f_i(x)$
4: **end for**
5: $F^* = [f_1^*, f_2^*, \dots, f_k^*]^T$
6: Find pay off matrix $\Phi(i, j)$:
7: **for all** $i, j \in \{1, \dots, k\}$ **do**
8: $\Phi(i, j) = f_i(x_i^*) - f_i^*$
9: **end for**
10: Finding efficient solutions set ES_{set}:
11: $ES_{set} \leftarrow \emptyset$
12: **while** stop criteria not reached **do**
13: Find $\beta \in \mathbb{R}^n : \sum_{i=1}^{n} \beta_i = 1, \beta_i \geq 0 \ \forall \ i \in \{1, \dots, n\}$
14: **for all** $i \in \{1, \dots, k\}$ **do**
15: point $P_i = (f_1(x_i^*),\, f_2(x_i^*), \dots, f_k(x_i^*))$
16: **end for**
17: Find the normal vector $\vec{n}$ of $P_i : i \in \{1, \dots, k\}$
18: Find x_e from P_e.
19: $ES_{set} \cup x_e$
20: **end while**
21: **return** ES_{set}

minimum value of each objective function. In the second part, lines 7-9, the Ideal Point is used to construct the pay off matrix. Finally, the third part is represented by lines 10-20 with a loop, in which efficient solutions are found. P_e, in line 18, is defined as the problem (1)-(3):

$$\max_{x_e, t} \quad t \tag{1}$$

$$\Phi\beta + t\hat{n} \;=\; F(x_e) - F^* \tag{2}$$

$$x_e \;\in\; X \tag{3}$$

For each β at constraint (2), an efficient solution will be found. An important step is how to find β. In a bi-objective case, $\beta = [\beta_1, \beta_2]^T$ can be calculated as following: $\beta_1 = \alpha$ and $\beta_2 = 1 - \alpha : \alpha \in [0, 1]$. Moreover, the value of α can be used as a stop criteria. Staring with $\alpha = 0$ and increment it, progressively, by $0 < \delta < 1$, the method terminates if $\alpha > 1$.

The NBI and ϵ-constraint methods are similar in at least two aspects. Firstly, they use parameters that are modified iteratively in order to construct an APF. Second, for both methods, once defined the parameters, the methods form a single objective optimization problem whose solution gives one efficient point.

Once an APF is found, there is a need to choose one solution that best fits the interests of the decision maker (DM). It could be difficult for the DM manually examine a large number of solutions to choose one. Thus, methods are available to reduce the number of efficient solutions to few ones, yet they represent well the APF: minimum distance from the ideal point with normalization and weights (MDIPNW) [36], TOPSIS [37], Promethee II [38], Fuzzy Algorithms (FA) [39],[40]. A comparison between some of these methods is proposed in [40].

Table 1: Summary of the characteristics used in some related works.

Reference	# of SHC models	APF	Selection in APF	Comfort model	Pricing	Objective
[6]	12	x	x	L	TOU	↓ D vs C
[41]	4	x	x	Q	TOU	↓ D vs C vs PAR
[42]	4			L	TOU-DA	↓ C vs D
[43]	0	x	x			↓ C vs E vs EL
[44]	0	x		Q		↓ D vs EU
[45]	0	x		Q		↓ D vs EU
[46]	4					↓ D vs C
[47]	2	x		-		↓ C vs E
[48]	6	x		L	TOU	↓ D vs C
[49]	1				RTP	↓ D vs C
[50]	1	x	x	L	RTP-DA	↑ OS vs ↓ WT
[50]	1	x	x	L	RTP-DA	↑ OS vs ↓ C
[50]	1	x	x	L	RTP-DA	↑ OS vs ↓ WT vs C
[51]	2	x		L	RTP	↓ WT vs C
[52]	3			Q	NC	↓ D vs C vs BL
[53]	1	x		L	NC	↓ D vs C
[54]	5	x		L	NC	↓ D vs C
[55]	2				RTP	↓ D vs C
[56]	8	x		NL	RTP	↓ D vs C
[57]	10	x		L	RTP	↓ PL vs C

3.3. MOO review in the context of smart houses

Table 1 summarizes papers using MOO in the context of smart homes. The first column of this table gives the literature sources, second column gives the number of specific and realistic models considered by each source. Columns *APF* and *Selection in APF* indicate, respectively, papers that found an APF and papers that chose a solution in it. Furthermore, column *Comfort model* expresses the way that comfort function was modeled, and column *Price type* gives the pricing policy considered. Finally, column *Objective* conveys the optimization objective(s). The abbreviations and symbols used are the following: TOU: time of use, RTP: real-time pricing, ↓: Minimize, L: Linear, Q: Quadratic, NL: Nonlinear, NC: not constant, DA: Day ahead, C: Cost, D: Discomfort, PL: Peak load, WT:Waiting time, E: Emissions, EL: Energy loss, PAR: Peak to average ratio, EU: Energy used, ↑: Maximize, OS: Operational safety.

Table 1 shows that the work in [6] uses realistic models for every individual SHC. These models are integrated into a mixed integer linear problem (MILP) that acts as a home energy management system scheduler for a consumer. Moreover, the work implements an approach that gives an APF and selects a solution in it. Only [6] in this table explores the investment aspect of smart homes.

4. Framework

Let SHC^- be the set of SHC that are not available at the current house. The goal is to compute economic evaluations of every combination in the set SHC^-. The proposed framework is represented by the Algorithm 2, which is composed of four parts. This algorithm is an extension of the approach presented by the authors in [6].

Algorithm 2 - Framework

1: Construct an APF for the Current House Problem with the trade-off: cost vs discomfort
2: Select an efficient point with coordinates (C′,D′)
3: Solve $SHP^c \ \forall \ c \subseteq SHC^-$ - Tree Algorithm
4: Compute economic evaluations

4.1. Construct an APF for the Current House Problem with the trade-off: cost vs discomfort

The householder has two conflicting objectives: minimize costs and discomfort level. Thus, instead of having only one optimal solution, there is a Pareto front of efficient solutions.

This work combines the multiobjective model from [6] with the strategy *Fraction of step* of [3], which allows SHC to operate during a fraction of the step time. For instance, let the variable $z_a^t \in \mathbb{R}_+$ be the fraction of the time step $t \in T$ during which appliance a is on and $y_a^t \in \mathbb{B}$ a binary variable that control on-off state of a at time step. Hence, $z_a^t y_a^t = z_a^t$. In this paper, the *Fraction of step* is applied for every SHC model of [6], except for the combined heat and power (CHP) model. Thus, the only appliance model that contains binary variables is the CHP model. This strategy keeps the solution quality and accelerates the optimization CPU time by removing binary variables: see [3] for details.

The final model schedules the energy consumption for one day in T time intervals with a fixed length of Δ. The appliances are grouped as follows:

- A: Set of electrical appliances;
- $A_I \subseteq A$: Set of appliances with uninterruptible operation;
- A_I^*: Set of tasks for appliances in A_I.
- $A_P \subseteq A$: Set of appliances with interruptible phases;
- A_P^*: Set of tasks for appliances in A_P;
- $A^* = \{A_P^* \cup A_I^*\}$: Set of tasks for appliances in A.

Let $\mathcal{X}$ be the feasible space of all variables and $\boldsymbol{\Xi} \in \mathcal{X}$ a solution. The functions f_c, f_t, f_u, and f_d represent, respectively, the total cost, the thermal discomfort, the usage-time discomfort, and the total discomfort:

- $f_c(\boldsymbol{\Xi}) = \sum_{t \in T} \left(C_b^t - C_s^t + C_{CHP}^t \right) + C_{ev}$,
- $f_t(\boldsymbol{\Xi}) = \sum_{t \in T} \sum_{a \in A} V_a^t$,
- $f_u(\boldsymbol{\Xi}) = r_1 \left[\sum_{k \in A_p^*} \sum_{p=1}^{P_k} \Psi_{k,p} + \sum_{k \in A_I^*} \zeta_k \right] + r_2 \sum_{t \in T} \sum_{k \in A^*} U_k^t$

where: a) as variables: C_b^t [\$] and C_s^t [\$] represent the cost at $t \in T$ of buying and selling energy, respectively, C_{CHP}^t [\$] is the combined heating power (CHP) operation cost at $t \in T$, C_{ev} [\$] is the fuel cost for a hybrid vehicle, V_a^t [^{o}C] is the discomfort related to the deviation from the target temperature of appliance a at $t \in T$, U_k^t [hour] is the discomfort related to the deviation from the target time for task k at $t \in T$, ζ_k [hour] is the discomfort related to the omission of task $k \in A_I^*$, $\Psi_{k,p}$ [hour] is the discomfort related to the omission of phase p of task $k \in A_P^*$; b) as parameters: P_k is the number of phases of task $k \in A_P^*$, $r_1 \in \mathbb{R}$ is the discomfort factor per task not performed and $r_2 \in \mathbb{R}$ is the discomfort factor per usage-time deviation.

Let define the "Current House Problem" as:

$$\min_{\Xi} \ [f_c(\Xi), f_d(\Xi) = \alpha_t f_t(\Xi) + \alpha_u f_u(\Xi)] \tag{4}$$

$$\Xi \in \mathcal{X} \tag{5}$$

where α_t [discomfort/^{o}C] and α_u [discomfort/hour] are discomfort factor parameters. The first step uses the optimization model (4)-(5) to compute an APF. In this model, beyond pricing and flow conservation constraints, only the constraints for available SHCs in the current house are considered to construct $\mathcal{X}$.

4.2. Select an efficient point with coordinates (C′,D′)

The next step is to select an efficient point on the APF, which can be done with Posteriori Decision in Multiobjective Optimization Methods (PDMOM) such as TOPSIS [37], MDIPNW [36] or PROMETHEE [38, 58, 59]. A comparison of some PDMOM is done in [40]. From now on, let's suppose the decision maker has selected a point with discomfort level D′.

4.3. Solve $SHP^c \ \forall \ c \subseteq SHC^-$ - Tree Algorithm

The discomfort level D' is used to create the constraint $C^d : f_d(\Xi) \leq D'$. For each subset $c \subseteq SHC^-$, the framework solves the optimization problem "Scenario House-c Problem (SHP^c)" with the constraint C^d and the constraint(s) related to the components in subset c. Moreover, the flow conservation constraint will be modified to consider the components from the current house in addition to the components of the subset c. If $SHC^- = \{$EV,WH,PV$\}$ and $c = \{$WH,EV$\}$, so the SHP^c is the following:

$$\min_{\Xi} \quad f_c(\Xi) \tag{6}$$

$$f_d(\Xi) \ \leq \ D' \tag{7}$$

$$\Xi \ \in \ \mathcal{X}_{\mathcal{EV}} \tag{8}$$

$$\Xi \ \in \ \mathcal{X}_{\mathcal{WH}} \tag{9}$$

$$\Xi \ \in \ \mathcal{X} \tag{10}$$

Objective Function (6) minimizes the consumer cost. Constraint (7) assures a maximum discomfort level D'. In Constraints (8) and (9), $\mathcal{X}_{\mathcal{EV}}$ and $\mathcal{X}_{\mathcal{WH}}$ means a set of feasible points for EV and WH, respectively. Thus Constraints (8) and (9) ensures operation constraints of the EV and the WH, respectively. Finally, (10) are the constraints considered on (5) with the adjustments of the flow conservation constraint to consider the EV and the WH.

The proposed framework differs mainly from [6] by the way that the problems $\text{SHP}^c\ \forall\ c \subseteq SHC^-$ are solved. While in [6] these problems are solved without any transfer of information among them, in the proposed framework the optimal solution from a previous problem is used as starting point for new problem resolution processes. This reuse of previous solutions is implemented through a tree data structure, which is defined as "Tree Algorithm".

4.3.1. Tree Algorithm

Suppose $SHC^- = \{WH, EV, CHP\}$. The first step in the Tree Algorithm sorts the set SHC^- in a lexicographical order. So, SHC^- results in the ordered set $SHC^+ = \{CHP, EV, WH\}$. Each node of the tree is associated with a subset $c \subseteq SHC^+$. In the algorithm, each node is represented by a tuple of data: an identity "*id*" and a set $c \subseteq SHC^+$. The notation $c[i]$ is used to specify the element $i : i \leq |c|$ of the set c.

The Tree Algorithm is summarized in Algorithm 3. Variables are initialized in lines 1-3. The root node is created at line 4. The root node considers a problem SHP^c with every SHC in SHC^+, so $c = SHC^+$. At line 5, the node whose id corresponds to the value of the variable "id" is selected and its corresponding set c is used to solve the SHP^c at line 6. Lines 7 to 11 create child nodes of the root node. Each child will contain a subset $c \subset SHC^+$ so that $|c| = |SHC^+| - 1$. In lines 13 to 30, a loop is executed. Each iteration of that loop solves one node. At line 18, if the current node has more than one element in its set, child or children may be created. Every node in the tree contains a different set $c \subseteq SHC^+$, which is guaranteed with a conditional test in line 22 by checking the variable "memorySet". The goal of the memorySet is to serve as a consulting buffer to eliminate the creation of nodes that contains an already existing set in some node of the tree.

Let's illustrate the execution of Algorithm 3 considering $SHC^+ = \{CHP, EV, WH\}$ throughout the Figures 3-6. In these figures, each block represents the state of the tree by the end of a specific line of the Algorithm 3. Each block contains, at left, the variable values; a region, at down, to represent the variable "memorySet"; the representation of the tree nodes; and a red letter "c" that represents the selected node. A node is represented by a circle with its id above it and its set inside it. Nodes represented by a dashed lines circle are nodes whose set c were already considered to solve SHP^c. Lines 4,5 and 6 of Algorithm 3 are simulated in Figure 3. By the end of line 6, the variable "memorySet" is empty and the root node is solved. In Figure 4, by the end of line 11, the root

Algorithm 3 Tree Algorithm

1: id,nSolve ← 0
2: i,counter ← 1
3: memorySet ← ∅
4: Create root node (id, SHC^+)
5: Attribute the set from node id to c
6: Solve SHP^c
7: **while** ($i \leq |c|$) **do**
8:     id ← i
9:     Create node (id,c/c[i]), child of c
10:     i ← i + 1
11: **end while**
12: counter ← i
13: **while** (nSolve $< 2^{|SHC^-|} - 2$) **do**
14:     nSolve ← nSolve +1
15:     id ← nSolve
16:     Attribute the set from node id to c
17:     Solve SHP^c
18:     **if** $|c| > 1$ **then** ▷ c create children of c
19:         i ← 1
20:         **while** ($i \leq |c|$) **do**
21:             id ← counter
22:             **if** c/c[i] ∉ memorySet **then**
23:                 Create node (id,c/c[i]), child of c
24:                 counter ← counter + 1
25:                 memorySet ← memorySet ∪ {c/c[i]}
26:             **end if**
27:             i ← i + 1
28:         **end while**
29:     **end if**
30: **end while**

node has three children: the first one has $c[1] = CHP$, so it has the set $c = SHC^+/CHP = \{EV, WH\}$; the second child has $c[2] = EV$, so it has the set $c = SHC^+/EV = \{CHP, WH\}$; and the other child has $c[3] = WH$, so it has the set $c = SHC^+/WH = \{CHP, EV\}$. The first iteration of the loop (13-30) solves the node with id=1, creates children of that node and adds two sets in the memorySet. In Figure 5, the second and the third iteration of the loop (13-30) are shown. In the second iteration, the node with id=2 does not generate the child $c/c[1] = \{WH\}$ because that set is already in the variable "memorySet". For the same reason, the node with id=3 does not generate any child in the third iteration. Finally, Figure 6 represents the fourth and the last iteration of the loop (13-30). In the fourth iteration, the node with id=4 is selected to be solved. As it has only one element in its set, there is no creation of any child. By the end of the last iteration of the loop (13-30), the last node is solved and when the line 13 is executed to begin a new iteration, the test $6 = nSolve < 2^{|SHC^-|} - 2 = 6$ is false, so Algorithm 3 terminates.

After the resolution of each parent node, the optimal solution for the parent is sent to every child to be used as

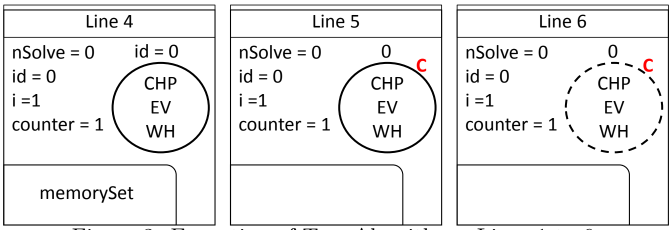

Figure 3: Execution of Tree Algorithm - Lines 1 to 6.

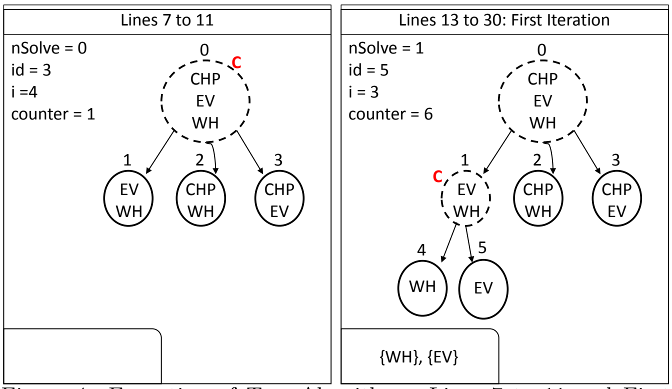

Figure 4: Execution of Tree Algorithm - Lines 7 to 11 and First iteration of loop 13-30.

an initial solution in the child problem. Each child problem has less or an equal number of constraints than the parent node problem. Thus, the feasible region of a child problem may be equal to or larger than the feasible region of a parent problem. An optimal solution for the parent problem may be close to an optimal solution for the child problem. Let's illustrate hypothetical convex hulls of two variables with their optimal solutions in Figure 7. In this figure, the yellow regions represent the feasible region of each node, the parent node has the optimal solution p and each child has the optimal solution represented by q. Each child takes a strict subset of SHC from the parent node, which means a subset of constraints from the parent node problem convex hull. The solution q for a given node may be near to the solution p. The gain of using a tree structure is to use a hot solution, for each node, as an initial solution for a specific algorithm: Interior Point [60]. The Interior Point solves linear and continuous optimization problems moving from an interior point of the feasible region towards an optimal extreme point.

4.4. Compute economic evaluations

The computation of economic evaluations is done in this step. Let's consider D^p as the project duration in years, Pay^B as the payback period, s^{slp} as the savings in the lifespan project, T^I as the total investment and I^R as the return on investment. Thus, payback is calculated accordingly to [5, Section 3.4] as $Pay^B = D^p T^I / s^{slp}$ and $I^R = s^{slp} - T^I$. Considering also C_t as the net cash inflow during the period t, C_o as the total initial investment costs and r as the required rate of return, the Net Present Value (NPV) is given by Equation (11). An investment with a negative NPV will result in a net loss.

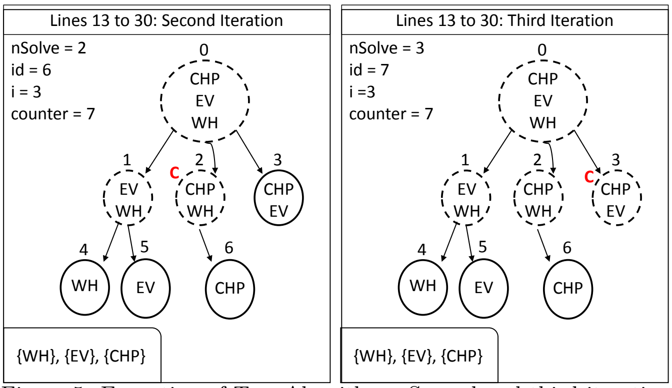

Figure 5: Execution of Tree Algorithm - Second and third iteration of loop 13-30.

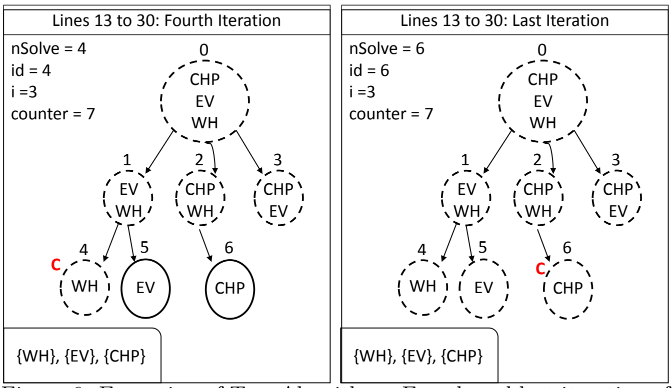

Figure 6: Execution of Tree Algorithm - Fourth and last iteration of loop 13-30.

$$NPV = \sum_{t=1}^{D^p} \frac{C_t}{(1+r)^t} - C_o \tag{11}$$

5. Results and Discussion

The work in [6] shows that the payback differs depending on site and application. Here, the goal is to decrease the CPU time issue from [6]. In addition, instead of payback period, NPV is used to determine the most profitable set of SHC to be acquired.

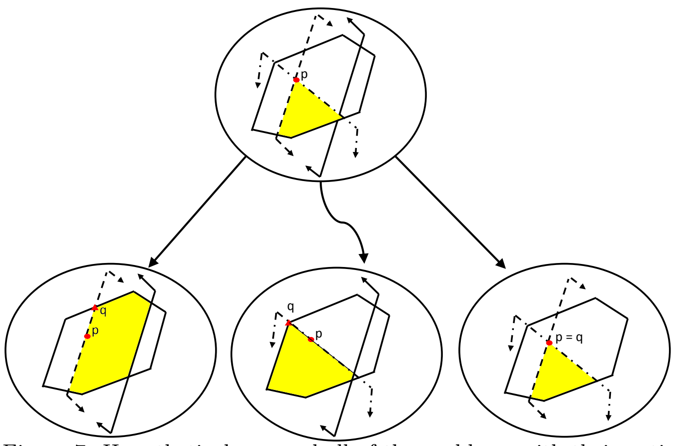

Figure 7: Hypothetical convex hull of the problems with their optimal solution.

The proposed framework is applied on 40 case studies that cover most of the Brazilian cities with considerable demographic density. For all of them, the analysis is done considering the exchange rate 1USD = 3.3BRL and a project duration of 25 years. As some SHCs have a life span lower than 25 years, the total cost has increased in proportion. For instance, if the component PV has a life span of 12.5 years, so one needs 2 units of that component to reach 25 years of project. Houses have appliances with distinct daily tasks A^t, a HVAC system, a shower and a fridge. The required rate of return is set to 12% yearly, which corresponds to the conservative investment rate of the Brazilian Treasury Prefixed Fund (*Tesouro Prefixado 2029*) [61] in July 2019.

Local inflation is not considered. This paper supposes that a customer wishes to acquire a system at the present time. For each case study, 1024 different systems are evaluated based on yearly savings approach. It means that, for each system, 365 days are optimized and the daily sum of savings composes the yearly savings. The total savings for a specific project is the multiplication of the yearly savings of that project by the project duration. For each SHP^c, the total investment is computed by summing up the total cost of each component that belongs to the set c considered. With cost and savings, economic measures can be computed with the formulas given in Section 4. For these examples, the goal is to discover what should be the SHCs to be acquired for these specific users in a profitable way.

For the appliances $a \in A_{IEUI} \cup A_{Phases}$, a dataset with real daily load profiles is available [62]. A set of load profiles is created for each day of the week. In the optimization, for each day of the week, a load profile from the corresponding set is randomly selected. Wind speed, solar radiation, thermal mass of building, etc., are considered in constraints proposed in [3], which are also used in this work. For more details, justifications and hypotheses for all decisions related to the SHC models are defined in [3]. We set $\alpha_u = \alpha_t = 1$.

For each case study, the house does not have μ-CHP, EV, WH, SC, WT, Battery and PV. Thus, we considered the $SHC^- = \{$PV 3.5kW, PV 6.5kW, Battery 26kWh, Battery 13kWh, WT 3kW, WT 7kW, SC, WH, EV, μ-CHP,$\}$. When similar components are in the same subset $c \subseteq SHC^-$, they are replaced by new similar component whose capacity is the sum of the capacities of the similar elements in c. The house considered does not have an infrastructure to receive natural gas, so an ICE is chosen as μ-CHP. The information about the set SHC^- is summarized in Table 2. In the table, each element of SHC^- is announced in the first column, its brand and model in the second column. The third column gives the warranty of the SHC, which is considered as its life span. Prices in dollars are given in the fourth column. These prices are converted to Brazilian currency (BRL) in the column "Price R$". Finally, the last column adds installation cost to the column "Price R$". Unless otherwise stated, maintenance costs are not considered: once the warranty ends, the SHC is replaced by a new one. The total daily distance trip for EV is drawn from the uniform distribution U[0,70]km. For solar radiation, the percentage of clouds for each month from [63] is considered. As an example, the percentage of clouds for each month for Belo Horizonte city is shown in Figure 8. It avoids an underestimation of solar radiation by considering always clear skies. Other parameters are set as indicated in [3].

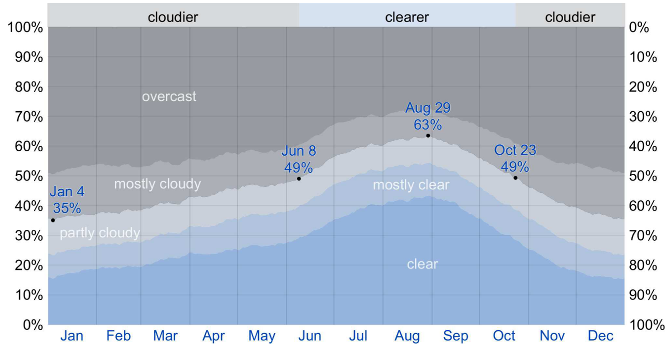

Figure 8: The percentage of time spent in each cloud cover band at BH, categorized by the percentage of the sky covered by clouds: clear < 20% < mostly clear < 40% < partly cloudy < 60% < mostly cloudy < 80% < overcast. Source: [63].

5.1. *Solving "Current House Problem" - APF Results*

The ϵ-constraint [32, Algorithm 1] is compared with the Normal-Boundary Intersection (NBI) [31] to solve the Current House Problem and to obtain an APF. The discomfort level was kept as objective function while cost became constraint. For ϵ-constraint method, we set $\delta = 0.5$ and for the NBI method, we set $\beta = 0.01$. The results are shown in Figures 9 and 10.

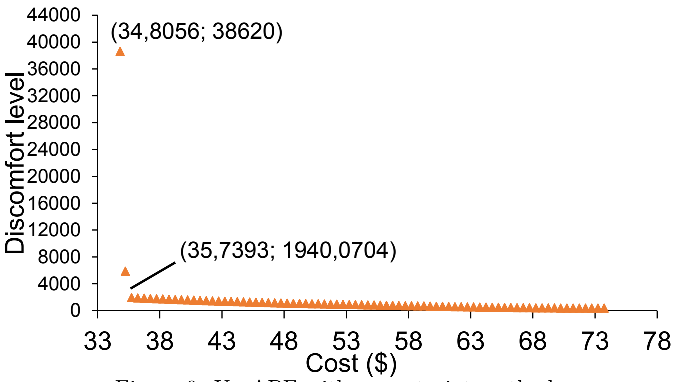

Figure 9: Un APF with ϵ-constraint method.

The total CPU time for ϵ-constraint method and NBI method were, respectively, 1794 seg. and 958 seg. From Figures 9 and 10, if the cost is constrained by a value less than 35.73$ there is a fast increase in discomfort level. The NBI found a huge amount of efficient points with cost between 35.73$ and 34.81$ and few efficient points for cost bigger than 35.73$ compared to ϵ-constraint. The advantage of CPU time for NBI is explained by the fact that problems with a budget lower than 35.73$ are easily solved since that many SHC are set to off. However, in practice,

Table 2: SHC Summary for BH case

SHC	Brand and Model	Life span (years)	Price (USD)	Price (R$)	Total Cost (R$)
PV 3.5kW	14 × CS CS5P-250M	25 [a]	14 × 225 [64]	11781 [b]	17671.50
Battery 26kWh	2 × Tesla Powerwall	10 [65]	12500 [65]	41250 [b]	61875
WT 3kW	3 × Bergey Excel 1kW	5 [a]	3 × 4995[c]	49450.5 [b]	74175.75
SC	Coupled Tempersol [66]	5 [a]		1400 [66]	2100
WH	Rheem 80G	10 [67]	1899 [67]	6266.7 [b]	9400.05
EV	2018 Nissan Leaf	5 [a]	30000 [68]	120000 [69]	120000
μ-CHP	Yanmar CP5WN-SNB	2 [a]		3950 [70]	5925
PV 6.5kW	26 × CS CS5P-250M	25 [a]	26 × 225 [64]	21879 [b]	32818.5
Battery 13kWh	1 Tesla Powerwall	10 [65]	6600 [65]	21780 [b]	32670
WT 7kW	Bergey Excel 1kW + Bergey Excel 6kW	5[a]	10000[c]	330000 [b]	49500
WT 10kW	Bergey Excel 10kW	10 [71]	31770[c]	104841 [b]	157261.5

a: According to the manufacturers's datasheet
b: Value converted from dollars USD to BRL
c: Given by the manufacturer
CS: Canadian Solar

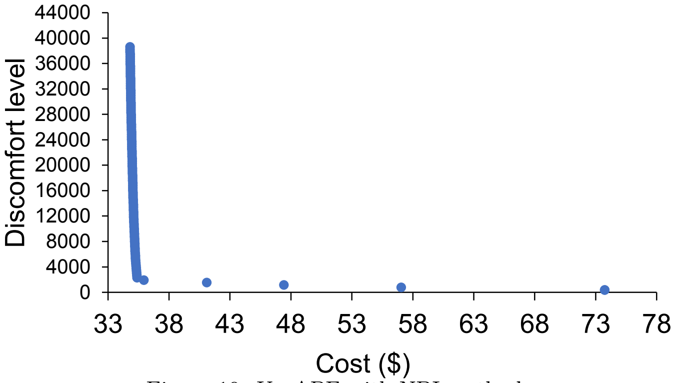

Figure 10: Un APF with NBI method.

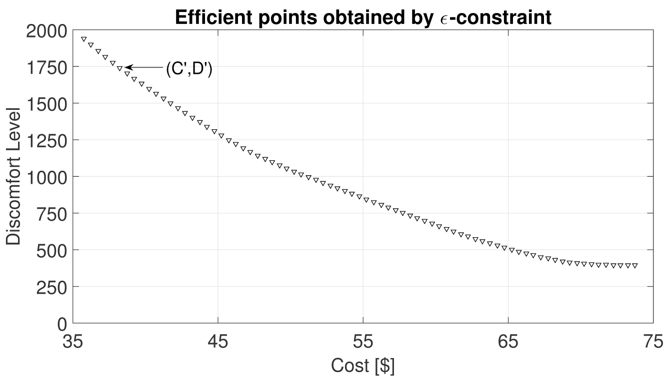

Figure 11: An APF and a chosen point to construct C^d.

a solution that prevents the use of many SHC will be less likely to be selected by the householder. In that sense, it is better to select the ϵ-constraint method to find an APF since it generates a more fairly dispersed set of efficient points for the APF compared to the NBI.

Removing solutions with cost lower 35.73$, a selection of one efficient point is needed as shown in Figure 11. The efficient solutions found in Figure 11 could be presented to the DM, but choosing one of them can be hard. Hence, methods such as MDIPNW, TOPSIS or Fuzzy methods can be used to decrease the number of available options, by modifying the weights for each criteria. Figures 12,13 and 14 show the efficient points found by some of those methods. The weights used to find the points are shown near them, except in Figure 13 to avoid information overlap. MDIPNW and fuzzy methods have a better dispersion of points than TOPSIS for the Current House Problem.

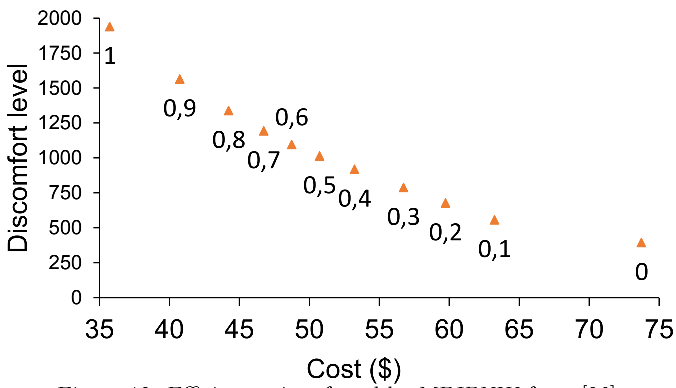

Figure 12: Efficient points found by MDIPNW from [36].

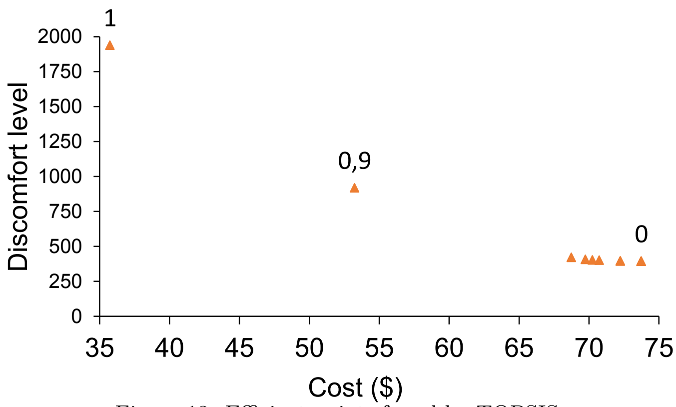

Figure 13: Efficient points found by TOPSIS.

This paper uses MDIPNW [36] to help select an efficient point with a coordinate (C',D'). Having this coordinate, one can create a constraint C^d to ensure a maximum level of discomfort, then solve $SHP^c \ \forall \ c \subseteq SHC^-$.

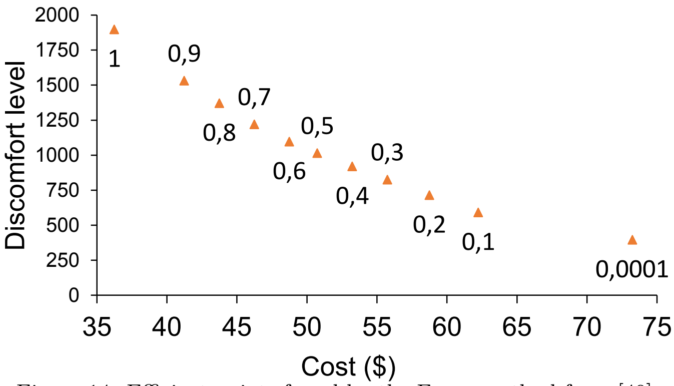

Figure 14: Efficient points found by the Fuzzy method from [40].

5.1.1. Belo Horizonte's house - Economic Measures

Due to space constraints, a compiled data-base for 40 Brazilian cities is available online[3]. The example of *Belo Horizonte* city is shown in this subsection. Table 3 summarizes some SHC combination results whose payback are lower than 25 years.

Table 3: Belo Horizonte results

System	Pay^B (years)	I^R (thousand R$)	NPV
PVs, 3.5 kW	10.7	23.7	-4.7
PVs, 6.5 kW	11.4	39.4	-10.1
PVs, 10 kW	12.4	51.3	-18.5
WTs, 7 kW	16.4	129.6	16.8
WTs, 10 kW	19.51	110.61	-58.9
SC	10.8	13.68	3.2
WH	11.0	29.7	3.7

Although systems composed only by PVs or by WTs-10 kW have a payback lower than the project duration and a positive I^R, the NPV shows that they are not worthwhile for this house. Thus, the computation of only payback and return on investment should be avoided.

For the case under consideration, batteries are too expensive and must be avoided. Every set c with battery has an NPV negative and lower than the respective set without battery. The price for one Tesla battery pack must decrease to around 1075.5 USD to pay itself off without any renewable generation. Systems composed by a battery and a renewable generation or SC have negative NPV. In the system WTs 7 kW and 13kWh battery, the battery's price must be around 4300 USD to have a positive NPV and around 2000 USD to match NPV of WT 7kW system alone. Systems with battery and SC have a negative NPV even if the battery lifespan is 25 years.

The EV is extremely expensive in the country. Its price must be at most 44850 R$ to worth the cost. If the decision maker is going to buy a car of price x R$, the price for a EV must be at most $x + 44850$ R$ to have a tie situation. If one considers a lifespan of 10 years for EV, the price must be at most 66600 R$ to have a positive NPV. Let's consider two scenarios with maintenance costs. In the first one, in the sixth year after the warranty, R$ 1000 was allocated for maintenance and this cost has been increased by R$ 300 for each subsequent year. A similar idea is applied in the second scenario until the 14^{th} year in which the EV is sold by R$ 20000 and a new one is bought. Then, from 15^{th} year until the 19^{th}, maintenance is zero, and in the 20^{th} an amount of R$ 1000 was allocated for maintenance and this cost has been increased by R$ 300 for each subsequent year. The NPV is -39.9 and -53.0 thousand of R$ for scenario one and two, respectively. The EV must cost around 80000 R$ for scenario one and 75000 R$ for scenario two in order to make NPV positive. Therefore, EV is not beneficial money-wise.

WH system is a better option for water heating because SC system has a positive NPV, but lower than: (i) the WH system; (ii) the WH and SC system. The system {μ-CHP, WH, SC} has a negative NPV. The μ-CHP does not pay itself in any case even if its price is reduced to half because of its short life span. The μ-CHP is profitable if its warranty or lifespan increases to 7 years.

For this householder, the set {WH, WT 7kW} gives the best NPV (18.9 k R$), the set with the smallest payback ({PV 3.5kW}) and the set with the highest return on investment ({PV 3.5kW, WH, PV 6.5kW, WT 7.5kW}) have a negative NPV.

5.1.2. Belo Horizonte's house - Time Efficiency

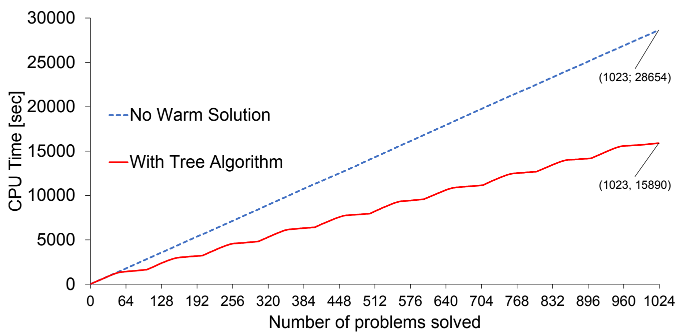

Figure 15: Cumulative CPU Time for one day.

A computer equipped with an 1.9 Ghz Intel Core i5-4300U CPU is used. Tree Algorithm has been applied in order to demonstrate the time that has been saved. In this demonstrations, only one computer core is used for a daily optimization of every system. The results are shown in Figure 15. Using Tree Algorithm, approximately 12764 seconds have been saved in total, which shows an improvement of 44.4% over the approach without a warm solution. The warm solution benefits nodes after the root node, so the resolution of those nodes contributes to the total savings, which explains the slope reduction for the cumulative time after the problem 64 with the Tree Algorithm. With Tree Algorithm, there is an increase in the slope due to two reasons: the selection of nodes nearer to the root node, which takes more time to be solved and the tree structure operation itself. Considering 365 days, four

[3] www.michaeldavidsd.com

computer cores were used by the solver. The total CPU time with no warm solution and with Tree Algorithm was 34.43 days and 19.40 days, respectively.

6. Conclusions

The number of smart homes is increasing worldwide. Transforming a home into a smart one requires considerable investment. Some consumers perceive the technology adoption towards smart homes as unprofitable [4]. Hence, householders face the following question: *Given a house, without some SHC (PVs, WT, WH, batteries, etc), what should be the SHCs to be acquired for a specific user in such way that will be profitable?* Available tools to answer that question needs a considerable amount of CPU time. The motivation of this paper is to answer the aforementioned question in a reasonable time. Thus, this paper proposes a framework to help the transition from current houses to smart homes considering customized electricity usage. The framework gives a NPV analysis of each possible acquisition combination of smart appliances or equipment for a specific user in a reasonable time. The proposed framework is tested on 40 cases: an online tool is available to access them. Focusing on one example, the steps and algorithms to be used in the framework implementation have been shown. The results show that NPV should be used as an economic measure rather than payback or return on investment in the context of transition towards smart homes. In addition, compared with the literature, the proposed framework can reduce days of CPU time to solve the problem.

References

[1] M. E. El-hawary, The smart grid—state-of-the-art and future trends, Electric Power Components and Systems 42 (3–4) (2014) 239–250. doi:10.1080/15325008.2013.868558.

[2] M. Fadaeenejad, A. M. Saberian, M. Fadaee, M. A. M. Radzi, H. Hizam, M. Z. A. AbKadir, The present and future of smart power grid in developing countries, Renewable and Sustainable Energy Reviews 29 (2014) 828–834. doi:10.1016/j.rser.2013.08.072.

[3] M. D. de Souza Dutra, M. F. Anjos, S. Le Digabel, A realistic energy optimization model for smart-home appliances, International Journal of Energy Research 0 (0). doi:10.1002/er.4454.

[4] A. Sanguinetti, B. Karlin, R. Ford, Understanding the path to smart home adoption: Segmenting and describing consumers across the innovation-decision process, Energy Research & Social Science 46 (2018) 274–283. doi:10.1016/j.erss.2018.08.002.

[5] M. N. Akter, M. A. Mahmud, A. M. T. Oo, Comprehensive economic evaluations of a residential building with solar photovoltaic and battery energy storage systems: An Australian case study, Energy and Buildings 138 (2017) 332–346. doi:10.1016/j.enbuild.2016.12.065.

[6] M. D. de Souza Dutra, M. F. Anjos, S. Le Digabel, A general framework for customized transition to smart homes, Energy 189 (2019). doi:10.1016/j.energy.2019.116138.

[7] K. Gur, D. Chatzikyriakou, C. Baschet, M. Salomon, The reuse of electrified vehicle batteries as a means of integrating renewable energy into the european electricity grid: A policy and market analysis, Energy Policy 113 (2018) 535–545. doi:10.1016/j.enpol.2017.11.002.

[8] S. Schopfer, V. Tiefenbeck, T. Staake, Economic assessment of photovoltaic battery systems based on household load profiles, Applied Energy 223 (2018) 229–248. doi:10.1016/j.apenergy.2018.03.185.

[9] S. van der Stelt, T. AlSkaif, W. van Sark, Techno-economic analysis of household and community energy storage for residential prosumers with smart appliances, Applied Energy 209 (2018) 266–276. doi:10.1016/j.apenergy.2017.10.096.

[10] H. J. J. Yu, A prospective economic assessment of residential pv self-consumption with batteries and its systemic effects: The french case in 2030, Energy Policy 113 (2018) 673–687. doi:10.1016/j.enpol.2017.11.005.

[11] M. D. Chatzisideris, P. K. Ohms, N. Espinosa, F. C. Krebs, A. Laurent, Economic and environmental performances of organic photovoltaics with battery storage for residential self-consumption, Applied Energy 256 (2019). doi:10.1016/j.apenergy.2019.113977.

[12] B. Bai, S. Xiong, B. Song, M. Xiaoming, Economic analysis of distributed solar photovoltaics with reused electric vehicle batteries as energy storage systems in china, Renewable and Sustainable Energy Reviews 109 (2019) 213–229. doi:10.1016/j.rser.2019.03.048.

[13] K. Uddin, R. Gough, J. Radcliffe, J. Marco, P. Jennings, Techno-economic analysis of the viability of residential photovoltaic systems using lithium-ion batteries for energy storage in the united kingdom, Applied Energy 206 (2017) 12–21. doi:10.1016/j.apenergy.2017.08.170.

[14] S. Kichou, N. Skandalos, P. Wolf, Energy performance enhancement of a research centre based on solar potential analysis and energy management, Energy 183 (2019) 1195–1210. doi:10.1016/j.energy.2019.07.036.

[15] K. Say, M. John, R. Dargaville, R. T. Wills, The coming disruption: The movement towards the customer renewable energy transition, Energy Policy 123 (2018) 737–748. doi:10.1016/j.enpol.2018.09.026.

[16] G. Coria, F. Penizzotto, R. Pringles, Economic analysis of photovoltaic projects: The argentinian renewable generation policy for residential sectors, Renewable Energy 133 (2019) 1167–1177. doi:10.1016/j.renene.2018.08.098.

[17] R. Espinoza, E. Muñoz-Cerón, J. Aguilera, J. de la Casa, Feasibility evaluation of residential photovoltaic self-consumption projects in peru, Renewable Energy 136 (2019) 414–427. doi:10.1016/j.renene.2019.01.003.

[18] E. O'Shaughnessy, D. Cutler, K. Ardani, R. Margolis, Solar plus: A review of the end-user economics of solar pv integration with storage and load control in residential buildings, Applied Energy 228 (2018) 2165–2175. doi:10.1016/j.apenergy.2018.07.048.

[19] Y. Xie, M. S. Gilmour, Y. Yuan, H. Jin, H. Wu, A review on house design with energy saving system in the UK, Renewable and Sustainable Energy Reviews 71 (2017) 29–52. doi:10.1016/j.rser.2017.01.004.

[20] M. Coffman, P. Bernstein, S. Wee, Integrating electric vehicles and residential solar pv, Transport Policy 53 (2017) 30–38. doi:10.1016/j.tranpol.2016.08.008.

[21] D. Mazzeo, Nocturnal electric vehicle charging interacting with a residential photovoltaic-battery system: a 3e (energy, economic and environmental) analysis, Energy 168 (2019) 310–331. doi:10.1016/j.energy.2018.11.057.

[22] T. Beck, H. Kondziella, G. Huard, T. Bruckner, Optimal operation, configuration and sizing of generation and storage technologies for residential heat pump systems in the spotlight of self-consumption of photovoltaic electricity, Applied Energy 188 (2017) 604–619. doi:10.1016/j.apenergy.2016.12.041.

[23] J. Linssen, P. Stenzel, J. Fleer, Techno-economic analysis of photovoltaic battery systems and the influence of different consumer load profiles, Applied Energy 185 (2017) 2019–2025. doi:10.1016/j.apenergy.2015.11.088.

[24] E. Zitzler, K. Deb, L. Thiele, Comparison of multiobjective evolutionary algorithms: Empirical results, Evolutionary Computation 8 (2) (2000) 173–195. doi:10.1162/106365600568202.

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

[26] K. Kuhn, A. Raith, M. Schmidt, A. Schöbel, Bi-objective robust optimisation, European Journal of Operational Research 252 (2) (2016) 418–431. doi:10.1016/j.ejor.2016.01.015.

[27] M. Ehrgott, X. Gandibleux, A survey and annotated bibliography of multiobjective combinatorial optimization, OR-Spektrum 22 (4) (2000) 425–460. doi:10.1007/s002910000046.
URL https://doi.org/10.1007/s002910000046

[28] R. T. Marler, J. S. Arora, Survey of multi-objective optimization methods for engineering, Structural and Multidisciplinary Optimization 26 (6) (2004) 369–395. doi:10.1007/s00158-003-0368-6.

[29] M. Ehrgott, Multicriteria optimization, Springer Science & Business Media, 2006.

[30] C. Filippi, E. Stevanato, A two-phase method for bi-objective combinatorial optimization and its application to the tsp with profits, 2012 7 (2) (2012).
URL https://journals.lib.unb.ca/index.php/AOR/article/view/20401/23539

[31] I. Das, J. E. Dennis, Normal-boundary intersection: A new method for generating the pareto surface in nonlinear multicriteria optimization problems, SIAM Journal on Optimization 8 (3) (1998) 631–657. doi:10.1137/s1052623496307510.

[32] M. Laumanns, L. Thiele, E. Zitzler, An efficient, adaptive parameter variation scheme for metaheuristics based on the epsilon-constraint method, European Journal of Operational Research 169 (3) (2006) 932–942. doi:10.1016/j.ejor.2004.08.029.

[33] G. Mavrotas, Effective implementation of the ϵ-constraint method in multi-objective mathematical programming problems, Applied Mathematics and Computation 213 (2) (2009) 455–465. doi:10.1016/j.amc.2009.03.037.

[34] H. W. Hamacher, C. R. Pedersen, S. Ruzika, Finding representative systems for discrete bicriterion optimization problems, Operations Research Letters 35 (3) (2007) 336–344. doi:10.1016/j.orl.2006.03.019.

[35] G. Chiandussi, M. Codegone, S. Ferrero, F. E. Varesio, Comparison of multi-objective optimization methodologies for engineering applications, Computers & Mathematics with Applications 63 (5) (2012) 912–942. doi:10.1016/j.camwa.2011.11.057.

[36] M. Clemente-Císcar, S. San Matías, V. Giner-Bosch, A methodology based on profitability criteria for defining the partial defection of customers in non-contractual settings, European Journal of Operational Research 239 (1) (2014) 276–285. doi:10.1016/j.ejor.2014.04.029.

[37] J. Malczewski, GIS and multicriteria decision analysis, John Wiley & Sons, 1999.

[38] J. P. Brans, P. Vincke, A preference ranking organisation method: (the promethee method for multiple criteria decision-making), Management Science 31 (6) (1985) 647–656.
URL http://www.jstor.org/stable/2631441

[39] M. A. Abido, A novel multiobjective evolutionary algorithm for environmental/economic power dispatch, Electric Power Systems Research 65 (1) (2003) 71–81. doi:10.1016/s0378-7796(02)00221-3.

[40] R. O. Parreiras, J. H. R. D. Maciel, J. A. Vasconcelos, The A Posteriori Decision in Multiobjective Optimization Problems With Smarts, Promethee ii, and a Fuzzy Algorithm, IEEE Transactions on Magnetics 42 (4) (2006) 1139–1142. doi:10.1109/tmag.2006.871986.

[41] D. Wang, X. Zhang, K. Qu, T. Yu, Z. Pan, Q. Liu, Pareto tribe evolution with equilibrium-based decision for multi-objective optimization of multiple home energy management systems, Energy and Buildings 159 (2018) 11–23. doi:10.1016/j.enbuild.2017.10.072.

[42] T. Sattarpour, D. Nazarpour, S. Golshannavaz, A multi-objective HEM strategy for smart home energy scheduling: A collaborative approach to support microgrid operation, Sustainable Cities and Society 37 (2018) 26–33. doi:10.1016/j.scs.2017.09.037.

[43] M. Narimani, Maigha, J.-Y. Joo, M. Crow, Multi-objective dynamic economic dispatch with demand side management of residential loads and electric vehicles, Energies 10 (5) (2017) 624. doi:10.3390/en10050624.

[44] R. Yang, L. Wang, Z. Wang, Multi-objective particle swarm optimization for decision-making in building automation, 2011 Ieee Power and Energy Society General Meeting (2011) 1–5doi:10.1109/pes.2011.6039221.
URL <GotoISI>://WOS:000297469602035

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

[46] W. Jidong, S. Zhiqing, Z. Yue, D. Jiaqiang, Optimal dispatching model of smart home energy management system (2012) 1–5doi:10.1109/ISGT-Asia.2012.6303266.

[47] T. Petkajee, D. Banjerdpongchai, Multi-objective approach to economic and environmental optimal operations of cogeneration for building energy management system (2013) 1–6doi:10.1109/ECTICon.2013.6559611.

[48] Y. Zhang, P. Zeng, S. Li, C. Zang, H. Li, A novel multiobjective optimization algorithm for home energy management system in smart grid, Mathematical Problems in Engineering 2015 (2015) 1–19. doi:10.1155/2015/807527.

[49] Y.-H. Lin, M.-S. Tsai, An advanced home energy management system facilitated by nonintrusive load monitoring with automated multiobjective power scheduling, IEEE Transactions on Smart Grid 6 (4) (2015) 1839–1851. doi:10.1109/tsg.2015.2388492.

[50] Y. F. Du, L. Jiang, Y. Z. Li, J. Counsell, J. S. Smith, Multi-objective demand side scheduling considering the operational safety of appliances, Applied Energy 179 (2016) 864–874. doi:10.1016/j.apenergy.2016.07.016.

[51] A.-H. Mohsenian-Rad, A. Leon-Garcia, Optimal residential load control with price prediction in real-time electricity pricing environments, IEEE Transactions on Smart Grid 1 (2) (2010) 120–133. doi:10.1109/tsg.2010.2055903.

[52] Z. Yang, K. Long, P. You, M.-Y. Chow, Joint scheduling of large-scale appliances and batteries via distributed mixed optimization, IEEE Transactions on Power Systems 30 (4) (2015) 2031–2040. doi:10.1109/tpwrs.2014.2354071.

[53] Y.-Y. Hong, J.-K. Lin, C.-P. Wu, C.-C. Chuang, Multi-objective air-conditioning control considering fuzzy parameters using immune clonal selection programming, IEEE Transactions on Smart Grid 3 (4) (2012) 1603–1610. doi:10.1109/tsg.2012.2210059.

[54] A. Agnetis, G. de Pascale, P. Detti, A. Vicino, Load scheduling for household energy consumption optimization, IEEE Transactions on Smart Grid 4 (4) (2013) 2364–2373. doi:10.1109/tsg.2013.2254506.

[55] Z. Zhuang, L. Won Cheol, S. Yoan, S. Kyung-Bin, An optimal power scheduling method for demand response in home energy management system, IEEE Transactions on Smart Grid 4 (3) (2013) 1391–1400. doi:10.1109/tsg.2013.2251018.

[56] A. Anvari-Moghaddam, H. Monsef, A. Rahimi-Kian, Cost-effective and comfort-aware residential energy management under different pricing schemes and weather conditions, Energy and Buildings 86 (2015) 782–793. doi:10.1016/j.enbuild.2014.10.017.

[57] E. Shirazi, S. Jadid, Cost reduction and peak shaving through domestic load shifting and DERs, Energy 124 (2017) 146–159. doi:10.1016/j.energy.2017.01.148.

[58] M. Behzadian, R. B. Kazemzadeh, A. Albadvi, M. Aghdasi, PROMETHEE: A comprehensive literature review on methodologies and applications, European Journal of Operational Research 200 (1) (2010) 198–215. doi:10.1016/j.ejor.2009.01.021.

[59] R. O. Parreiras, J. A. Vasconcelos, A multiplicative version of promethee ii applied to multiobjective optimization problems,

European Journal of Operational Research 183 (2) (2007) 729–740. doi:10.1016/j.ejor.2006.10.002.

[60] S. Mehrotra, On the implementation of a Primal-Dual Interior Point Method, Siam Journal on Optimization 2 (4) (1992) 575–601. doi:10.1137/0802028.
URL <GotoISI>://WOS:000209499400003

[61] Ministério da Fazenda, Tesouro Nacional, accessed May 2018.
URL http://www.tesouro.fazenda.gov.br/tesouro-direto

[62] J. Kelly, W. Knottenbelt, The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes, Scientific Data 2 (2015) 150007. doi:10.1038/sdata.2015.7.

[63] Weatherspark.com, Average weather, accessed May 2018.
URL https://weatherspark.com/countries

[64] GoGreenSolar, Water heating cost, accessed Apr. 2018.
URL https://www.gogreensolar.com/products/canadian-solar-cs5p-250m-250-watt-solar-panel

[65] Tesla, Powerwall, accessed Apr. 2018.
URL https://www.tesla.com/powerwall?redirect=no

[66] TemperSol, Coupled tempersol, accessed Apr. 2018.
URL https://www.tempersol.com.br/produtos/

[67] Rheem, Rheem, accessed Apr. 2018.
URL https://www.homedepot.com/p/Rheem-Performance-Platinum-80-Gal-10-Year-Hybrid-High-Efficiency-Electric-Tank-Water-Heater-XE80T10HD50U0/300620269

[68] Nissan, Nissan Leaf 2018, accessed Apr. 2018.
URL https://www.nissanusa.com/electric-cars/leaf/versions-specs/version.s.html

[69] UOL, EV cost estimation, accessed Apr. 2018.
URL https://motor1.uol.com.br/news/184672/nissan-leaf-brasil-2019/

[70] Hikari, Gerador Diesel 6kW, accessed Apr. 2018.
URL http://www.hikariferramentas.com.br

[71] Bergey, Bergey Excel 10kW, accessed Apr. 2018.
URL http://bergey.com/products/wind-turbines/10kw-bergey-excel