A preference-based multi-objective demand response mechanism

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***Abstract*—The demand response (DR) aims to balance the purveyance and demand of electricity to maximize the reliability and efficiency of the energy supply process in the electrical power system (EPS). However, one of the main impediments to the insertion of DR in the residential context is the need of programming the use of various electrical appliances and the scheduling of renewable resources and storage system in the same time interval, that requires a range of specific knowledge and time availability of the consumer to handle the various home appliances. This article presents a preference-based multi-objective optimization model based on real-time electricity price to solve the problem of optimal residential load management. The proposal's purpose is to minimize both the electricity consumption associated cost and the inconvenience caused to consumers. The proposed model was formalized as a nonlinear programming problem subject to a set of constraints associated with the consumption of electrical energy and operational aspects related to the residential appliance categories. The proposed multi-objective model was solved computationally by the Constrained Many-Objective Non-Dominated Sorted Genetic Algorithm (NSGA-III) to determine the new scheduling of residential appliances, renewable energy resources, and energy storage system utilization for the entire time horizon, considering consumer preferences. The results show that the multi-objective DR model proposed using the NSGA-III technique can minimize the total cost associated with energy consumption as well as reduce the inconvenience of consumers, besides helping consumers to take advantage of DR's benefits without requiring manual intervention.**

***Index Terms*—demand response, microgrid, NSGA-III, optimization, smart grid**

I. Introduction

The global population increase has caused a greater complexity in the electricity supply. Therefore, studies and researches on the efficiency and reliability of electric power systems are necessary to avoid interruptions in the supply of electricity and the increase in prices, among other problems [1], [2].

At the same time, the depletion of conventional energy sources worldwide and the concern for the environment are also increasing rapidly [3]. One of the solutions to help overcome such problems is to incorporate an advanced measurement infrastructure, combined with information and communication technologies and smart meters through a smart grid (SG). An SG is a system that applies information and communication technologies (ICT) to improve the interaction between all the devices of an electrical power system (EPS) and consumers connected to it [4]. This interaction can be used by end consumers to improve their electricity consumption patterns to reduce the cost associated with electricity consumption.

The authors in [5] state that the demand response control methodologies and smart appliances can optimize the use of electrical resources more efficiently. In this sense, the authors in [6], [7] defined a demand response (DR), in a SG context, as a program that provides various incentives and benefits to end consumers to change their electricity consumption patterns in response to changes in the electricity price over time or when electrical power network reliability is compromised by any EPS overhead. The most common DR programs are based on price, in which a tariff model is used to help the user to adjust their electricity consumption patterns in response to electricity price deviation.

Based on the previous definition of DR, it could be a well-adopted concept on microgrids. A microgrid (MG) can be described as a cluster of distributed energy resources (DER), renewable energy resources (RRES), energy storage systems (ESS), and local loads, that can operate connected to the main grid or in islanding mode [8]. The MG allows for more efficient, reliable, and environmental-friendly energy production, by increasing the deployment of distributed generation (DG), especially through RRES, as well as distributed ESS [9], [10].

Although MG energy management has been studied with several different approaches in recent studies, as maximizing revenue of microgrid and minimizing environmental pollution [11], [12], improving dynamic performance by considering economic aspects [13], optimizing operation cost and economic performance [14], [15], and improving reliability of microgrid [16], as well as DR problems, such as [17], [18], [19], [20], [21], a preference-driven optimization mechanism and the scheduling of residential loads considering the different operating characteristics of the different categories of home appliances has not been well analyzed.

As the programming of the home appliances within the same time interval and the scheduling of RRES and the ESS requires time and specific knowledge on the part of the consumer [22], and the residential management scheduling must take into account consumer preferences regarding the use of these appliances and the price variation of electricity, in this paper, a preference-based multi-objective programming model is for

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energy management in a microgrid. The proposed model aims to optimize consumption cost and consumer satisfaction in a simultaneous way. A typical basic microgrid is studied, where the production side includes a photovoltaic panel (PV) system as a renewable energy resource and an ESS. *Constrained Non-Dominated Sorted Genetic Algorithm* (NSGA-III) [23] algorithm is applied to solve the proposed multi-objective problem. Several simulations, case studies, and comparative studies are carried out to demonstrate the efficiency and viability of the proposed methodology.

II. METHODOLOGY

This section presents the multi-objective DR optimization model solved using the Constrained NSGA-III algorithm to manage the loads of all the appliances, taking into account the real-time pricing (RTP) [24] structure, the operational characteristics of each appliance, the renewable energy resources, and the energy storage system. The basic concepts of Constrained NSGA-III, which is the technique used to solve the problem, are also presented.

A. Problem Modelling

The multi-objective DR optimization model proposed in this work has two objective functions: $f1$ and $f2$. The first one ($f1$) is related to the costs associated with the electricity consumption, and the second ($f2$), with the cost associated with the inconvenience caused to the end consumers concerning the optimized planning of the use of home appliances provided by the multi-objective model.

The function $f1$ used in the proposed multi-objective model, is formulated as follows:

$$\begin{aligned} Minimize \sum_{i=1}^{N} E_i \sum_{t=1}^{T} (Pr_t * DSA_{t,i})^2 \\ *(1-(DSRRES_{t,i}-DSESS_{t,i})^2) \end{aligned} \tag{1}$$

where N is the number of home appliances; $E_i (i = 1, \dots, N)$ represents the vector for the electrical energy consumption of home devices i when in operation; T is the time horizon; Pr_t is the price of electricity at time t. $DSA_{t,i}$ (Daily Setup of Appliances), $DSRRES_{t,i}$ (Daily Setup of Renewable Energy Resources), and $DSESS_{t,i}$ (Daily Setup of Energy Storage System) are binary matrix with the daily setup of operation of home appliances, renewable energy resources and energy storage system, respectively. $DSA_{t,i}$ refers to the load scheduling matrix with the following configuration:

$$DSA_{t,i} = \begin{cases} 1, & \text{if appliance } i \text{ is on at time } t, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

The $DSRRES_{t,i}$ refers to the planning matrix of RRES, and has the following configuration:

$$DSRRES_{t,i} = \begin{cases} 1, & \text{if appliance } i \text{ is consuming power from RRES at time } t, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The $DSRRES_{t,i}$ defines the scheduling of home appliances that consume power from RRES. In this work, RRES is composed of a system of photovoltaic panels (PVs) installed in the consumer's house. PV output power depends on cells temperature and solar irradiance at maximum power point (MPP) situation, expressed in (4) [25]. The temperature of the *m*-th cell of the PV is calculated by (4), and then the output power of PV at each time *t*, $t = 1, ..., T$ can be achieved by (5) [25]. Equation (6) corresponds to the inequality constraint for ensuring that the consumption of renewable energy by home appliances is lower than or equal to the output power of the photovoltaic system.

$$\begin{aligned} T_m(t) = T_{amp} + \frac{G_T(t)}{G_{T_{STC}}} * (NOCT - 20), \\ t = 1, ..., T \end{aligned} \tag{4}$$

$$\begin{aligned} P_{PV}(t) = ([P_{PV,STC} * \frac{G_T(t)}{G_{T_{STC}}} * (1 - \gamma * (T_m(t) - T_{mSTC}))] \\ *N_{PVs} * N_{PVp}), t = 1, ..., T \end{aligned} \tag{5}$$

$$\sum_{i=1}^{N} E_i * DSRRES_{t,i} \le P_{PV}(t), t = 1, ..., T \tag{6}$$

The $DSESS_{t,i}$ refers to the scheduling matrix of energy storage system (ESS), defined as:

$$DSESS_{t,i} = \begin{cases} 1, & \text{if appliance } i \text{ is consuming power from ESS at time } t, \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

The $DSESS_{t,i}$ defines the scheduling of home appliances that utilize power from the ESS. In this work, ESS is composed of a system of batteries, connected to the photovoltaic panels (PV), installed in the consumer's house. The ESS acts as a storage of electrical energy generated by the PV system, as well as a source of power for the home appliances when the energy prices are high [26]. Model of energy storage system are shown through (8)-(14) [27].

$$P_{ESS}(t) = E_S(t) - E_S(t-1), t = 1, ..., T \tag{8}$$

$$E_S^{min} \le E_S(t) \le E_S^{max}, t = 1, ..., T \tag{9}$$

$$\begin{aligned} E_S^{min} - E_S(0) \le \sum_{k=1}^{t} (P_{ESS}(k)) \le E_S^{max} - E_S(0), \\ t = 1, ..., T \end{aligned} \tag{10}$$

$$E_S(0) = E_S(T) \tag{11}$$

$$-\omega_C^E * P_{ESS}(t) \le P_{E-char}^{max}, t = 1, ..., T \tag{12}$$

$$\frac{P_{ESS}(t)}{\omega_D^E} \le P_{E-disch}^{max}, t = 1, ..., T \tag{13}$$

$$\sum_{i=1}^{N} E_i * DSESS_{t,i} \leq P_{ESS}(t), t = 1, ..., T \tag{14}$$

where $E_S(t)$ is the energy stored in the battery at time *t*; $P_{ESS}(t)$ is the battery's output power at time *t*; E_S^{min} and E_S^{max} are the minimum/maximum battery stored energy's boundaries, respectively. (8) states that the output power of the battery can not be greater than the current stored energy. (9) shows that the energy in the batteries must be limited between the minimum and maximum levels to avoid lifetime reduction of the batteries. At each time interval t, the $P_{ESS}(t)$ must be between these limits. Charging and discharging powers at each time *t* are limited by the actual energy stored in the battery, as shown in (10). The initial and final state of the battery load must be the same as described by (11). The limitation on charging/discharging for the batteries in the ESS are shown in (12) and (13). (14) states that the consumption of energy provided by the ESS must be less than or equal to its output power.

The function $f2$ measures the inconvenience and evaluates how the optimized scheduling of home appliances can modify the satisfaction/comfort of the final consumer and is given by

$$\begin{aligned} Minimize \sum_{t=1}^{T} \sum_{i=1}^{N} (Incv_{t,i}^{hourly}(DSA_{t,i}) \\ + Incv_{t,i}^{thermal}(DSA_{t,i})) \end{aligned} \tag{15}$$

(15) evaluates the consumption cost associated with two types of inconvenient situations, previously defined by the consumer. The higher the cost calculated through (15), the greater the inconvenience, expressed in monetary values based on the energy price coming from the utility and in how far the scheduling is of the desired by the consumer. These situations are expressed through operating hours and thermal conditions that each appliance must meet, as defined by the consumer.

The inconvenience is defined in two ways: the hourly inconvenience and the thermal inconvenience. The hourly inconvenience calculates the electricity consumption-associated cost in which home appliances are used at inconvenient times, according to the operational profile defined by the consumer. Such profile is composed of two arrays, $Profile\_Time$ e $Profile\_Req$, that allow the home appliances to operate with multiple starting/ending times. Each home appliance i has a $Size\_Profile_i$, which represents the number of different operating times defined for that specific home appliance. Based on that, the hourly inconvenience is defined by the $Incv_{t,i}^{hourly}(DSA_{t,i})$ function and is given by:

$$Incv_{t,i}^{hourly}(DSA_{t,i}) = \begin{cases} Pr_t * (ST_i^j - t) * DSA_{t,i}, & \text{if } t < ST_i^j, \\ 0, & \text{if } ST_i^j \leq t \ \leq ET_i^j, \\ Pr_t * (t - ET_i^j) * DSA_{t,i}, & \text{if } t > ET_i^j. \end{cases} \tag{16}$$

Where $j = 1, ..., Size\_Profile_i$.

The thermal inconvenience calculates the consumption cost at which the home appliances are used under inadequate/inconvenient thermal conditions as defined by the consumer. It's given by $Incv_{t,i}^{thermal}(DSA_{t,i})$ function, with the following configuration:

$$Incv_{t,i}^{thermal}(DSA_{t,i}) = \begin{cases} Pr_t * (Tem_t^{\underline{des}} - Tem_t^{in}) * DSA_{t,i}, & \text{if } Tem_t^{in} < Tem_t^{\underline{des}}, \\ 0, & \text{if } Tem_t^{\underline{des}} \leq Tem_t^{in} \leq Tem_t^{\overline{des}}, \\ Pr_t * (Tem_t^{in} - Tem_t^{\overline{des}}) * DSA_{t,i}, & \text{if } Tem_t^{in} > Tem_t^{\overline{des}}. \end{cases} \tag{17}$$

Where $Tem_t^{\underline{des}}$ and $Tem_t^{\overline{des}}$ are the min/max desired indoor temperature at time *t*, respectively; Tem_t^{in} is the indoor temperature at time *t*, calculated as follow [28]:

$$\begin{aligned} Tem_t^{in} = Tem_{t-1}^{in} + \alpha * (Tem_t^{out} - Tem_{t-1}^{in}) \\ + \beta * DSA_t^i * E_i, t = 1, ..., T, i = 1, ..., N \end{aligned} \tag{18}$$

Where Tem_t^{out} is the external temperature; α and β are thermal conditions surrouding the thermal home appliance.

With both objective functions defined, the best solution is one in which the home appliances are working as close as possible to the desired situation defined by the consumer and, at the same time, reducing the electricity consumption-associated cost. The closer the schedule is to the desired one, the better the solution.

The objective functions $f1$ and $f2$ are subject to the following constraints:

Constraint 1 (19) establishes the boundaries (minimum and maximum) for the load levels at each time interval t:

$$d_t^{min} \leq \sum_{i=1}^{N} DSA_{t,i} * P_i \leq d_t^{max}, t = 1, ..., T, \tag{19}$$

where d_t^{min} is the minimum demand for the load levels at each time interval t; $P_i (i = 1, \ldots, N)$ is the vector with the power (in kW) of each home appliance; d_t^{max} is the maximum demand for the load levels at each time interval t.

Constraint 2 (20) states that the load shifting between adjacent hours should not exceed the ramping down/up limits:

$$r^D \leq \sum_{i=1}^{N} (DSA_{t+1,i} - DSA_{t+1,i}) * P_i \leq r^U, t = 1, ..., T-1, \tag{20}$$

where r^D/r^U corresponds to the minimum/maximum ramp limit for the time interval t.

Constraint 3 (21) defines the minimum daily electricity consumption ($mdec$):

$$\sum_{i=1}^{N} \sum_{t=1}^{T} DSA_{t,i} * E_i \geq mdec. \tag{21}$$

The constraints 1–3 (19–21) refers to the power consumption common characteristics. As previously mentioned, the operation of home appliances with multiple start/end times must be allowed, so it is necessary to define some appliance-operating constraints.

To control the operation of the home appliances, two arrays, called $Profile\_Time$ and $Profile\_Req$, as previously stated, are defined. $Profile\_Time_i$ indicates an array of pairs in the format (starting time, ending time), for each home appliance i, $i = 1, ..., N$. In general, it can be defined as follows:

$$Profile\_Time_i = [(ST_1, ET_1), ..., (ST_j, ET_j)] \tag{22}$$

where $j = 1, ..., Size\_Profile_i$.

$Profile\_Req_i$ represents a numerical vector, with values representing the operating time of each home appliance i, $i = 1, ..., N$, according to the starting and ending times defined in the $Profile\_Time_i$ of the respective home appliance i, defined as follows:

$$Profile\_Req_i = (Req_1, ..., Req_j) \tag{23}$$

where $j = 1, ..., Size\_Profile_i$.

The following restrictions link and limit the $Profile\_Time$ and $Profile\_Req$ vectors. (24) defines the length of the vectors; (25) and (26) relate the values of both vectors and avoid overlapping of operating hours, respectively; (27) and (28) define that the maximum operation time of the home appliances should not be greater than the time horizon.

$$\begin{gathered} |Profile\_Time_i| = |Profile\_Req_i|, \\ |Profile\_Req_i| = Size\_Profile_i, \\ i = 1, ..., N \end{gathered} \tag{24}$$

$$\begin{gathered} ET_i^j - ST_i^j \geq Req_i^j, \\ i = 1, ..., N, j = 1, ..., Size\_Profile_i \end{gathered} \tag{25}$$

$$\begin{gathered} ET_i^j \leq ST_i^{j+1}, \\ i = 1, ..., N, j = 1, ..., Size\_Profile_i - 1 \end{gathered} \tag{26}$$

$$\sum_{j=1}^{Size\_Profile_i} Req_i^j \leq T, i = 1, ..., N \tag{27}$$

$$ET_i^{Size\_Profile_i} - ST_i^1 \leq T, i = 1, ..., N \tag{28}$$

In this work, the home appliances are divided into three categories based on their operational characteristics [29], which are: interruptible and deferrable (A_I); uninterruptible and deferrable (A_{II}); and, uninterruptible and non-deferrable (A_{III}). Uninterruptible refers to an operation that cannot be interrupted until completed. Deferrable and Non-deferrable state whether the operation must begin at the first time slot defined as the start time for the home appliance, or not. The constraints that deal with the different categories of home appliances A_I, A_{II} and A_{III} are based on these definitions and are specified below.

Constraint 5 (Equation (29)) states that the operational startup of category A_I home appliances may vary over the time defined by each pair (ST_i^j, ET_i^j) defined by the consumer, provided that Req_i^j is respected:

$$\sum_{t=ST_i^j}^{ET_i^j} DSA_{t,i} \geq Req_i^j, i \in A_I, j = 1, \ldots, Size\_Profile_i \tag{29}$$

where Req_i^j is the required time for appliance i to finish its operation in the interval defined by (ST_i^j, ET_i^j); A_I is a set of indices of the device categories interruptible and deferrable.

Constraint 6 (Equation (30)) states that the operational startup of category A_{II} home appliance can be delayed within the interval (ST_i^j, ET_i^j), but, once it has started, it cannot be interrupted:

$$\begin{gathered} \sum_{q=ST_i^j}^{ET_i^j - Req_i^j} \prod_{t=q}^{Req_i + q} DSA_{t,i} \geq 1, \\ \forall_i \in A_{II}, j = 1, \ldots, Size\_Profile_i \end{gathered} \tag{30}$$

where q is initial time slot of the interval that will be checked if the category A_{II} home appliances was used; A_{II} is the set of indices of the home appliance categories uninterruptible and deferrable.

Constraint 7 (Equation (31)) establishes that the operation of a category A_{III} home appliance between its startup (ST_i) and end (ET_i), as defined by the consumer, is uninterruptible and non-deferrable for the required time Req_i in the time horizon T:

$$\prod_{q=ST_i^j}^{ET_i^j} DSA_{t,i} \geq 1, \forall_i \in A_{III}, j = 1, \ldots, Size\_Profile_i \tag{31}$$

where ST_i is start time of the operation; ET_i is final time of the operation; A_{III} is the set of indices of the device categories uninterruptible and non-deferrable.

B. NSGA-III

In this study, the Constrained NSGA - III, proposed in [23], was adapted to tackle the multi-objective price-based DR problem. Every chromosome is a combination of the three binary matrices presented in Section II (DSA, $DSRRES$, and $DSESS$) and represents a possible schedule in the problem. The dimensionality of each matrix depends on the number of appliances N, and the time horizon T.

The constrained NSGA-III was designed to face up to many objectives at the same time (more than three), besides handling constrained problems, and is similar to the original NSGA-II algorithm [30], despite significant changes in its selection operator. But, unlike NSGA-II, the maintenance of diversity among population members in NSGA-III is aided by supplying and adaptively updating some well-spread reference points [23]. A brief presentation of the NSGA-III structure is presented as follows.

Determination of reference points on a hyper-plane: A set of reference points must be defined to ensure the diversity of the obtained solutions. Different points are placed on a normalized hyper-plan that have the same orientation in all the axis. The number of reference points (H) in an M-objective problem is given by:

$$H = \binom{M+p-1}{p} \tag{32}$$

Where p is the number of divisions to consider on every objective axis (for three objectives and four divisions, we will have 15 reference points), the reference points are placed on the hyper-plan, and the solutions are described by a Pareto front. Each solution is associated with the created reference points.

Normalization of the population members: An ideal point of the currently population must be determined, so the minimal value of each objective function ($OF_i^{min}, i = 1, 2, ..., C$) must be identified. Then, each objective function is translated by subtracting $z_i^{min} = (OF_1^{min}, OF_2^{min}, ..., OF_C^{min})$ to the objective f_i. The steps proposed by [23] are followed in order to generate a hyper-plan (solving the Pareto fronts where the objective solutions are different scale).

Association among reference points and solutions: After normalizing each objective function, it is necessary to associate each population member with a reference. It is defined as a reference line for each point, joining the reference point with the origin point. Then, the perpendicular distance between each population member and each reference line is determined. Finally, the reference point that has the closest reference line from a population individual is associated with his population member.

Niche preservation operation: A reference point can be associated with one or more solution members, but the solution that is closer to the point (perpendicular distance from the reference line, [23]) must be kept.

Genetic operators: The children's generation has been made applying the genetic operators used in the NSGA-II [30] algorithm. The population size was fixed close to the number of reference points (H) to give the same importance to all the population members.

III. Results and discussion

In this section, the results of computational simulations are presented in order to evaluate the performance of the proposed multi-objective optimization model of DR using the constrained NSGA-III optimization technique.

A. Case Study

In the simulation scenario, families composed of 02 adults without children were considered. The pattern of electrical energy consumption for each family was acquired through *Load Profile Generator (LPG)* [31] for 3 Brazilian families living in the cities of Brasília (DF), Florianópolis (SC) and João Pessoa (PB) located in the Center-West, South and Northeast regions of Brazil respectively.

A time horizon of T, with hourly discretization, was used in the computational simulations, which includes the days with highest and lowest electrical energy consumption for each family between January 1, 2016 and December 31, 2016. Is assumed that the entire scheduling time interval consists of 24 subintervals, that is, $t = \{1, 2, ..., 24\}$. Thus, the price of unit energy consumption in each time interval is based on the values of Portugal's Electricity Market (OMIE) to calculate the price of electricity for each hour, since Brazil does not use a DR program based on real-time electricity prices (RTP). The Home Energy management System (HEMS) proposed in [32] was used as an architecture in which the multi-objective DR model proposed in this paper is responsible for determining the load scheduling and the cycle of charge/discharge of ESS.

TABLE I
Optimal cost reduction per city

City	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
Brasília-DF	341.09	259.23	24.00
João Pessoa-PB	347.32	260.49	25.00
Florianópolis-SC	294.62	220.96	25.01

B. Simulation Results

In this work, we use the reference point scheme to found only a few solutions on a preferred part of the Pareto-Optimal front [23]. It acts as a way to represent consumer preferences in the optimization process, helping in the decision-making.

As defined by Jain and Deb in [23], to find a preferred set of solutions, a set of reference points (Rp) in the consumer preference region must be supplied. In addition, M extreme reference points $(1, 0)^T, (0, 1)^T$ are included, to make the normalization process to work well and make a total of $|Rp| + M$ reference points, that is the set P of reference points. These extreme points are needed to ensure that the ideal and nadir points [33] [34] of the population members are properly calculated for the normalization purpose in the NSGA-III algorithm. In the simulations, three reference points (set Rp) are used, in the middle of the normalized hyper-plane, as shown in Figure 1. As stated previously, two more extreme points (set M) are added to make a total of five reference points (set H). The crossover and mutation probability used were 0.6 and 0.1, respectively; the Population had eight chromosomes, and the maximum number of iterations was 700.

In Figure 2, the non-normalized Pareto-optimal solutions obtained are shown. These solutions were analyzed considering the energy consumption pattern of each family, obtained through LPG.

Table I presents the simulations results obtained for each family, taking into account the extreme point related to the objective of cost minimization, that is related to the Pareto-optimal solution for this objective. Thus, it is possible to observe that the family resident in the city of Florianópolis-SC obtained the best result concerning the total reduction of electricity consumption cost, going from R$ 294.62 to R$ 220.96, totaling a decrease of 25.01 %.

Table II presents the simulations results obtained for each family, taking into account the extreme point related to the objective of inconvenience minimization, which is related

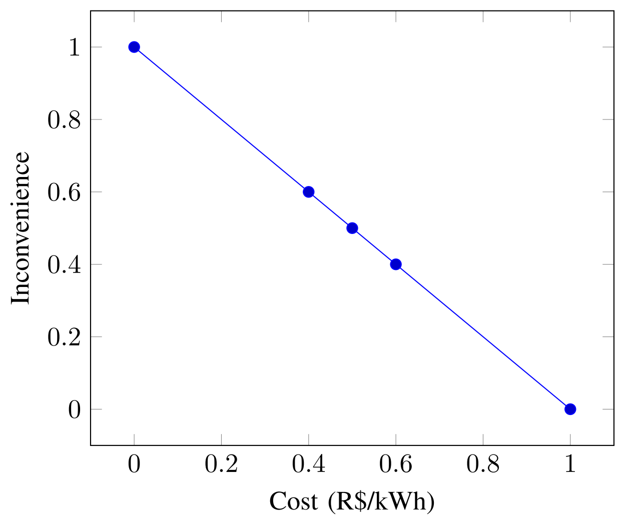

Fig. 1. A preferred set of reference points find corresponding Pareto-optimal solutions for the DR problem

to the Pareto-optimal solution for this objective. Thus, it is possible to observe that the family resident in the city of João Pessoa-PB obtained the lowest inconvenience-associated cost, with R$ 0.29.

TABLE II
OPTIMAL INCONVENIENCE PER CITY

City	Inconvenience (R$)
Brasília-DF	0.3
João Pessoa-PB	0.29
Florianópolis-SC	0.3

The labeled solution as ”A” in Figure 2 is the solution closest to the optimal point (0, 0). This solution presents the best tradeoff between the values of the two objectives formulated in the DR problem presented in this work. The cities of João Pessoa-PB and Florianópolis-SC obtained identical results in the cost minimization objective, with a total decrease of 24.1 % on consumption cost. In contrast, in the minimizing inconvenience objective, the city of João Pessoa-PB obtained the lowest inconvenience-associated cost, with R$ 0.81. The results obtained in the A-solution are presented in Tables III and IV.

TABLE III
A-SOLUTION COST REDUCTION PER CITY

City	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
Brasília-DF	341.09	259.62	23.9
João Pessoa-PB	347.32	260.88	24.1
Florianópolis-SC	294.62	221.35	24.1

C. RRES and ESS impact

The impact of the RRES and ESS on the results obtained in the simulation were also analyzed. A scenario without a PV system and ESS was simulated, and the DR model was

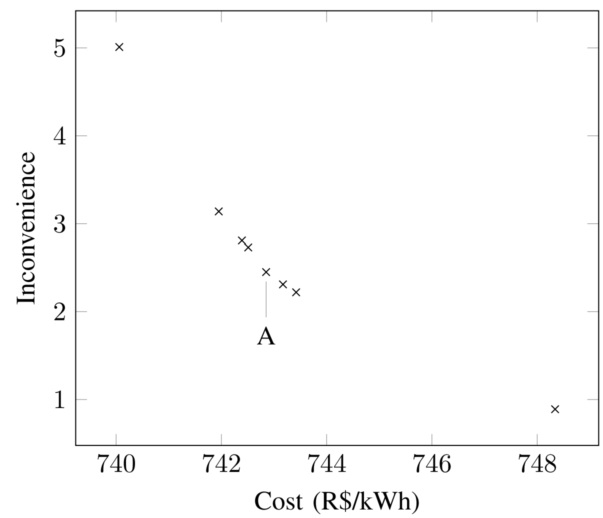

Fig. 2. Non-normalized Pareto-optimal solutions.

TABLE IV
A-SOLUTION INCONVENIENCE PER CITY

City	Inconvenience (R$)
Brasília-DF	0.82
João Pessoa-PB	0.81
Florianópolis-SC	0.82

adapted to handle these changes. The Equation 1 was changed to the following:

$$Minimize \sum_{i=1}^{N} E_i \sum_{t=1}^{T} (Pr_t * DSA_{t,i})^2 \tag{33}$$

The constraints (4-6) and (8-14) were not considered in this simulation. The Pareto-optimal solution related to the extreme point of the cost minimization objective of both simulation were compared. Table V shows that the optimal cost of the new simulation is, at least, 13.4% higher than the optimal cost obtained in the previous simulation, as occurred in the city of Brasília-DF, with an increment of R$ 34.79 in the consumption cost. In contrast, the city of João Pessoa-PB obtained a 15.2% increase in the electricity consumption-associated cost, totaling R$ 39.60.

TABLE V
COMPARISON BETWEEN SCENARIO WITH AND WITHOUT RRES ANS ESS.

City	Cost with RRES and ESS (R$)	Cost without RRES and ESS (R$)	Increment (R$)	Increment (%)
Brasília-DF	259.23	294.02	34.79	13.4
João Pessoa-PB	260.49	300.10	39.60	15.2
Florianópolis-SC	220.96	252.49	31.53	14.2

D. Statistical Analysis

The results from the experiments of home appliance scheduling were analyzed by three performance metrics: Diversity, Coverage, and Hypervolume. Diversity [35] measures the number of different solutions obtained by an algorithm in a search space between extreme solutions (maximum/minimum solutions of each objective function). Thus, a high number of solutions found in the search space means there are a high number of options available for decision-making.

The Coverage (metric C) is used to evaluate the optimal approach capability [36] of the solutions, which is the (theoretical) distance between the current Pareto Frontier and the theoretical optimal Pareto Frontier. Thus, based on its theoretical properties [36], Coverage ensures a space of solutions closer to the theoretical optimum to solve the DR problem.

Simulations with the R-NSGA-II are used to calculate the Coverage metric. The R-NSGA-II was proposed in [37], and it is a combination of the classical NSGA-II algorithm with a multi-criterion decision-making approach to not find a single optimal solution, but to find a set of solutions near the desired region of decision-makers interest [37]. The R-NSGA-II is compared to the NSGA-III optimization technique; therefore, the C [36] metric is used to determine which of the methods (NSGA-III or R-NSGA-II) has the best Coverage. The Hypervolume (HV) metric [36], [38], is used to determining the overall performance of the two techniques (NSGA-III or R-NSGA-II) in more detail. Both NSGA-III and R-NSGA-II were performed 1000 times to reduce the impact of their stochastic nature and to obtain the values to be used in the statistical analysis.

1) Statistical Results: The NSGA-III optimization technique results were compared with those from the R-NSGA-II to validate the correctness of the algorithm (*sanity check*). Diversity values showed that the NSGA-III algorithm (minimum 18.21 and maximum 22.3) had a greater diversity of solutions than the R-NSGA-II (minimum 12.25 and maximum 18.25). Therefore, the NSGA-III had better search space exploration, and this translates into a better comprehension of the objectives considered in the problem.

In the metric C, the values obtained for both $C(A, B)$ and $C(B, A)$ indicate that, in all cases, the Pareto frontier solutions found by the NSGA-III completely dominated the frontier solutions of Pareto found by R-NSGA-II. This result shows that the NSGA-III presents better solutions than the R-NSGA-II, considering the Pareto frontier of both techniques.

Additionally, the analysis of the Hypervolume values indicates a significantly better general performance of NSGA-III (minimum 0.91 and maximum 0.92) concerning R-NSGA-II (minimum 0.72 and maximum 0.83). This information, as previously mentioned, reflects better performance, in terms of convergence and extension, of the solution considering the search space [36]. Therefore, both the NSGA-III and R-NSGA-II enable the load scheduling to provide electricity costs reduction, as well as minimize the inconvenience caused to the end consumers appropriately. Table VI shows the statistical values for the simulations.

TABLE VI
STATISTICAL ANALYSIS.

Algorithm	Metric	Min	Max	Average	Std Deviation
NSGA-III	Spacing	18.21	22.30	19.46	1.02
R-NSGA-II		12.25	18.25	14.98	1.05
NSGA-III R-NSGA-II	C(A, B)	1	1	1	0
NSGA-III R-NSGA-II	C(B, A)	0	0	0	0
NSGA-III	HV	0.91	0.92	0.906	0.01
R-NSGA-II		0.72	0.83	0.77	0.02

CONCLUSIONS

This paper proposes a multi-objective DR optimization model to manage the scheduling of home appliances, with various categories, in a microgrid environment. The proposal aims at minimizes both electricity consumption-associated costs, as well as the inconvenience (dissatisfaction/discomfort) of end consumers while considering renewable energy resources (RRES) and an energy storage system (ESS). The scheduling of home appliances on smart grids allows the EPS to be more efficient and effective because problems such as power interruptions during peak demands can be minimized. Thus, DR plays a significant role in managing energy consumption to avoid overhead as well as reduce the electricity consumption-associated cost to end consumers.

The performance of the proposed DR optimization model was evaluated through simulations. First, the efficiency in minimizes both the energy consumption-associated cost as well as inconvenience (dissatisfaction/discomfort) of end consumers, considering some preference points given by the consumer, was analyzed. Also, the multi-objective model was adapted to handle the same DR problem without including RRES and ESS systems, to verify the influence of such resources to reduce the electricity consumption-associated cost. Next, through the Diversity, Coverage, and Hypervolume metrics, the solutions for the problem of scheduling the home appliances found by the constrained NSGA-III and the R-NSGA-II were evaluated. The results of the study showed that there is a significant reduction in the total cost associated with the consumption of electric power, allied with a low inconvenience-associated cost caused to all the families considered in the simulation scenario.

Besides, the statistical results in Table VI show that, when the NSGA-III technique is applied, it obtained the best results of the simulations when compared to the R-NSGA-II for all the metrics (Diversity, Coverage, and Hypervolume) used in this work.

Future research could further improve in several directions. One possibility would be to include electric vehicles and more renewable resources for the electrical energy generation in the optimization model. Another alternative could be to minimize environmental pollution as an objective in the optimization model. A third option is to implement the proposed model in an in-home display to use the proposal in an edge computing scenario.

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