Gravitational Search Algorithm Applied for Residential Demand Response Using Real-Time Pricing

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Abstract. This paper has as main objective the performance evaluation of the Gravitational Search Algorithm for Demand Response programs applied to residential consumers. For this purpose, it was considered a model that describes the consumption and energy price, according to the loads present in a residence. This way, it is intended to minimize the cost of electricity for final consumers based on an optimized planning of their loads at different times. In addition, it will be considered a variable cost of electricity over time (hourly price). In this sense, the cost of electricity will be discretized throughout the day. Finally, the performance of the Gravitational Search Algorithm for the considered model will be evaluated.

Keywords: Demand response · Gravitational Search Algorithm · Metaheuristic · Optimization · Smart grids

1 Introduction

One of the main functions of the Demand Response area is to ensure the minimization of the cost of electricity to consumers, encouraging them to plan their consumption in response to price changes over a period of time. In addition, this area emerged as a possibility to economically stimulate consumers, inducing them to use electricity more effectively. Therefore, it is expected that the methodologies focused on the context of Demand Response will enable the reduction of consumption, especially at peak times or when the reliability of the electrical system is compromised [1]. Thus, the Demand Response area plays a crucial role in the context of Smart Grids and in the energy markets [2]. Moreover, compared to the high value that is spent on the power systems infrastructure, the Demand Response can be considered as a low investment [3].

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In accordance with the aforementioned aspects, demand response programs can be divided into, basically, two groups [4]: based on the energy price, which are focused on the electricity market; and, based on consumer incentive, that analyze the loads and sources of energy.

It is noteworthy that demand response programs based on the energy price have the first objective to correlate the energy price to possible changes in the planning and usage profile of consumers' loads [4,5]. However, the benefits obtained by consumers through demand response programs can be optimized. Based on this premise, some researches have been devoted to characterizing the loads of the consumers and to use such information as a reference to integrate the energy consumption and thus to minimize energy price.

In [6], the authors propose an approach for demand response programs that is autonomous and distributed among consumers, taking advantage of a network communication infrastructure. Thus, another objective, besides minimizing the energy price, is to reduce the ratio between peak demand and average demand. It is noticed that this model takes into account a known function. So, this function considers the energy price throughout the planning horizon and the demand divided based on the consumers' loads.

The authors of [7] propose a robust demand response model that considers the uncertainty of energy usage during a 24-hour planning period. Thus, the utility informs the user about the price of the subsequent hour with a few minutes in advance. In this way, historical prices were used in the past hours to define the likely bands for the energy price in subsequent hours.

In the demand response model proposed by [8], the authors consider the consumption of electricity associated with each load used by the consumer and the forecast of the future energy price based on the price history on each day of the week. In addition, in the considered scenarios, the consumer has the option to set priorities for loads.

Following the above context, this paper intends to analyze the performance of Gravitational Search Algorithm using data provided by the Load Profile Generator (LPG) [9] software. Thus, the mathematical model proposed in [6] will be considered. It is worth mentioning that this paper will concentrate its efforts on a model of demand response based on the energy price, since one of the motivations of this choice is the current Brazilian energy scenario, which has operated in the red tariff rate since the beginning of the year 2015. Beyond that, the use of the Gravitational Search Algorithm is analyzed because of the practicality proportioned by this metaheuristic optimization algorithm, which have few parameters to set, does not make use of first and second order partial derivatives and is not dependent on the initial value of the iterative process.

The remaining of this paper is organized as follows. The simulated power consumption residential profiles, used as the basis for the parameterisation of the demand response optimization model, is presented in Sect. 2. The considered demand respond optimization model, proposed by [8], is briefly presented in Sect. 3. The fundamentals of the Gravitational Search Algorithm are presented in Sect. 4. Section 5 presents the results and discussions and, at last, Sect. 6 presents the conclusions and main contributions of this paper.

2 Simulated Residential Profiles

Several factors are capable of directly influencing the consumption profile of a residential consumer, among which it is possible to highlight: weather, time of year, loads used, presence of generators or energy storage (such as photovoltaic panels and batteries), number of residents, as well as the behaviour of these residents in relation to the energy consumption. In addition, the residential consumption profile has a more flexible characteristic compared to the industrial profile, allowing for adjustments and modifications by the consumer (without compromise their comfort).

In order to establish a reliable database consisting of consumption profiles for different scenarios of residential consumers, which are close to the current Brazilian scenario, the software LPG [9] was used. The LPG allows to configure the model of a residence with the desired load and profiles of residents. Thus, these profiles of consumption could be simulated in the desired period of time with a discretization of up to 1 min. It should be noted that the LPG is able to provide a complex modeling, taking into account the geographical location of the residence, time of year and temperature profile in the period of time evaluated.

Through the LPG, for the modeling of a residence with two adults and one child, it was possible to obtain a simulated consumption profile, using the loads described below:

- Bathroom - bulb lamps, hear dryer, and shower;
- Room - bulb lamp, video game console, and TV;
- Kitchen - bulb lamp, electric oven, food mixer, cooktop, microwave, electric clock, air purifier, juicer, food processor, toaster, coffee machine, electric kettle, electric fondue maker, refrigerator, and mixer;
- Living room - bulb lamp, computer, monitor, video game console, TV, printer, scanner, router, stereo, and notebook;
- Laundry - vacuum cleaner, washing machine, and electric iron.

3 Optimization Model

The optimization model to be considered in this paper is the one proposed by [6], where it is considered an autonomous and distributed demand response program. This program considers a certain group of nearby consumers, taking advantage of a bidirectional communication infrastructure that is a strong tendency of the Smart Grids.

Each consumer belonging to the group has an Energy Consumption Scheduler (ECS), responsible for making intelligent measurements, managing the flow of information between consumers and executing the algorithm to minimize the final cost of energy. It is noteworthy to mention that, in this model, the energy prices are communicated to the consumers with antecedence corresponding to the entire scheduling horizon. Therefore the optimization process does not require any price prediction method. Another objective of the proposed model is to reduce the Peak-to-Average Ratio (PAR), since the latter objective indicates the quantity of demand in the peak period. This, is a very important factor that contributes to increase or decrease the energy price.

By calling η the group of consumers fed by the same source, the number of consumers is $N \doteq |\eta|$. The discretization considered in this case is one hour. For each consumer $n \in \eta$, l_n^h denote the total energy consumption at the hour $h \in [1, 2, ..., H]$, where $H = 24$. Thus, the daily load profile for the user n is denoted as $l_n \doteq [l_n^1, ln^2, ..., ln^H]$. Based on these definitions, the total hourly consumption considering all the users can be computed as follows:

$$L_h \doteq \sum_{n \in \eta} l_n^h \tag{1}$$

The peak consumption and the mean daily consumption can be respectively computed as follows:

$$L_{peak} = max(L_h), h \in [1, 2, ..., H] \tag{2}$$

$$L_{mean} = \frac{1}{H} \sum_{h \in [1,2,...,H]} L_h \tag{3}$$

Thus, the peak to average ratio can be computed as:

$$PAR = \frac{L_{peak}}{L_{mean}} = H \frac{max(L_h)}{\sum_h (L_h)}, h \in [1, 2, ..., H] \tag{4}$$

For each consumer, A_n denotes the set of appliances present in the residence. Thus, for each load $a \in A_n$, the power consumption planning vector is given by $x_{n,a} \doteq [x_{n,a}^1, ..., x_{n,a}^H]$, where $x_{n,a}^h$ denotes the consumer's planned energy consumption n for the load a in hour h. In this way, the total hourly consumption of each consumer can be obtained as follows:

$$l_n^h \doteq \sum_{a \in A_n} x_{n,a}^h, h \in [1, 2, ..., H] \tag{5}$$

It is worth noting that in this model, daily energy consumption planning does not aim to change the total amount of energy consumed, but rather to manage and allocate it in order to reduce the PAR or minimize the total cost paid by the consumer. In this case, the consumer must select the start $\alpha_{n,a} \in [1, 2, ..., H]$ and the end $\beta_{n,a} \in [1, 2, ..., H]$ of a time interval in which each appliance can be triggered. The definition of these time intervals impose a set of constrictions to the power consumption planning vector, so the total daily consumption must occur within the set interval. Thus, the total daily consumption is defined as follows:

$$\sum_{h \in [\alpha_{n,a}, \beta_{n,a}]} x_{n,a}^h = E_{n,a} \tag{6}$$

$$x_{n,a}^h = 0, \forall h \in [1, 2, ..., H] \backslash [\alpha_{n,a}, \beta_{n,a}] \tag{7}$$

For each appliance, the use time defined by the consumer must be greater than the time interval required for the appliance to properly perform its function. It is possible to notice by (6) and (7) that, in order to maintain the energy balance, the consumption of all loads powered on must be equal to the sum of the total pre-set consumption of each load. Aditionally, the standby power consumption $\gamma_{n,a}^{min}$ and the maximum operating power consumption $\gamma_{n,a}^{max}$ are defined the for each appliance of each consumer. Thus:

$$\gamma_{n,a}^{min} \leqslant x_{n,a}^{h} \leqslant \gamma_{n,a}^{max}, \forall h \in [\alpha_{n,a}, \beta_{n,a}] \tag{8}$$

Finally, the minimization problem of energy costs can be represented as follows:

$$min(\sum_{h\in[1,2,\ldots,H]} (p^h \sum_{n\in N} \sum_{\alpha\in A_n} x_{n,a}^{h}) + \lambda_{PAR} \max_{h\in[1,2,\ldots,H]} (\sum_{\eta\in N} \sum_{\alpha\in A} x_{n,a}^{h})), \tag{9}$$

where H denotes the set of hours belonging to the planning horizon; N denotes the set of residences belonging to the considered group; A_n denotes the set of loads belonging to the residence n; P^h is the energy cost in hour h; $X_{n,a}^{h}$ is the planned energy consumption for the residence n during hour h; and λ_{PAR} is a parameter used to weight the impact of PAR minimization on the fitness function. It is worth mentioning that in this paper, the value assigned to the parameter λ_{PAR} is equal to 1.

4 Foundations of Gravitational Search Algorithm

The Gravitational Search Algorithm (GSA) was introduced in 2009 by [10], which is based on the law of universal gravitation. In GSA, the search agents constitute a set of objects that interact with each other through Newton's gravitational force and the laws of motion.

In this way, all particles in the universe attract each other. In addition, the intensity of this attraction is a direct effect of the mass of the particles and the proximity between them. It is worth mentioning that the gravitational constant has a decreasing behaviour over time.

The GSA can be seen as an artificial universe of agents that obey the laws of universal gravitation and Newtonian mechanics. Therefore, agents with larger masses represent better solutions. In this sense, each agent of the GSA has two variables (position and mass). The position of each agent corresponds to a feasible solution of the problem, while the value of its mass is determined by means of the fitness function used. In this context, the better the agent's aptitude, the greater his mass, and consequently the greater the attraction he will exert on the other agents and the slower he will move through the search space. The mass of each agent is calculated according to the following equations:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best_i(t) - worst(t)} \tag{10}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{11}$$

where $fit_i(t)$ denotes the fitness of agent i at iteration t; $worst(t)$ and $best(t)$ are the values of the worst and best fitness, respectively, obtained among all agents at iteration t.

At the iteration t, for each coordinate, the force that acts over the agent i because of the mass of the agent j is computed as follows:

$$F_{ij}^d(t) = G(t)\frac{M_i(t)M_j(t)}{R_{ij}(t)+\epsilon}[X_j^d(t) - X_i^d] \tag{12}$$

where $M_i(t)$ and $M_j(t)$ are the masses of agents i and j, respectively, at iteration t; G(t) is the value of the gravitational constant at iteration t; ϵ is a constant very close to zero; and $R_{ij}(t)$ is the Euclidean distance between agents i and j at iteration t.

With the intention of guaranteeing a stochastic characteristic to the algorithm, the component on the coordinate d of the acceleration force acting over the agent i is defined as a randomly weighted sum of all the components on the coordinate d of the forces exerted by the other agents:

$$F_i^d(t) = \sum_{j=1, j\neq i} rand \times F_{ij}(t) \tag{13}$$

where $rand$ is a random number within the interval [0, 1].

Consequently, the acceleration component of the agent i on the coordinate d at iteration t is computed as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{14}$$

This way, the velocity of agent i at iteration $t+1$ is equal to the sum of its current acceleration with a random portion of its velocity at the previous iteration (t):

$$v_i^d(t+1) = rand \times v_i^d(t) + a_i^d(t) \tag{15}$$

From the current velocity calculated by (15) and the position occupied by the agent in the previous iteration, its new position is then computed as follows:

$$X_i^d(t+1) = X_i^d(t) + v_i^d(t+1) \tag{16}$$

Thus, the optimization process performed by the GSA consists in adjusting the masses of the objects so that they move through the search space and, at the end of the iterations, occupy the position corresponding to the best solution. The GSA should follow a sequence of procedures presented on Fig. 1.

5 Results

In the analyzed test case, due to the fact that the optimization model considers all the appliances independently, the use time constraints $\alpha_{n,a} \in [1, 2, ..., H]$ and

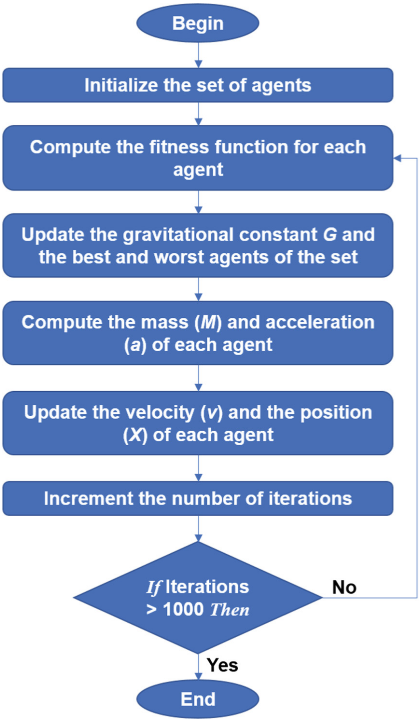

Fig. 1. Flowchart of the Gravitational Search Algorithm.

$\beta_{n,a} \in [1, 2, ..., H]$ for each one of the appliances $a \in A_n$ were defined based on the simulations conduced using the LPG. Beyond that, the test case has consisted on a group of three household, each one with 40 identical appliances. The considered energy prices was the hourly prices informed by the Iberian Energy Market Operator [11] in January 15^{th}. According to the number of residences, the number of loads, the power constraints and the use time constraints defined by Eqs. (6)–(8) based on the LPG simulated consumption profile presented in Fig. 2, it was possible to determine the size and limits of the search space used by the GSA agents. Each dimension of the search space represents the consumption of one of the 40 loads of one of the three residences in one of the 24 h of the planning horizon. In this way, the number of dimensions is equal to 2880. Thus, the GSA was empirically parameterized to have 50 agents and the stopping criterion is adjusted to 1000 iterations. The fitness function used in the GSA was the one that represents the minimization problem of energy costs (9). At the end of the iterations, the GSA returns the energy consumption planning matrix with the minimum price to be paid at the end of one day.

At this point, it is important to state that the novelty of this paper, compared with the work in [6], is the use of a metaheuristic optimization algorithm to minimize the energy cost and serve as a decision support tool for the end consumer.

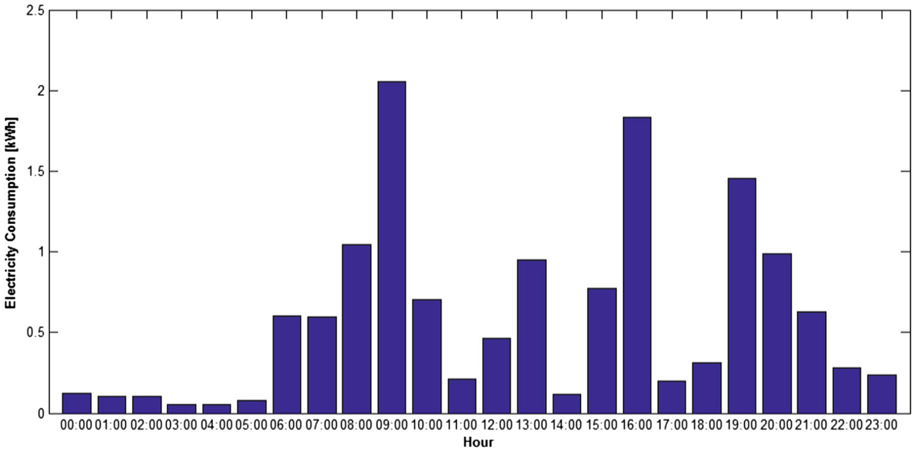

Fig. 2. LPG simulated consumption profile.

The optimized individual consumption planning of each residence of the group in question, obtained for the one-day planning horizon, can be observed in Fig. 3.

As can be seen from Fig. 3, the three residences belonging to the group have individual optimized schedules totally different from each other, with demand peaks at times other than the planning horizon. This characteristic is associated

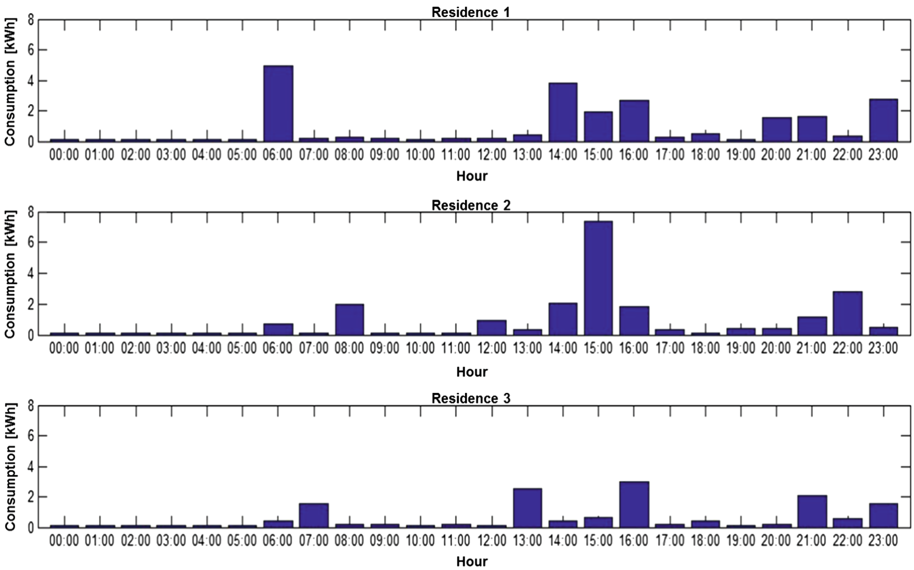

Fig. 3. Optimized planning of consumption for each residence.

with the fact that the model in question has as one of its objectives the minimization of PAR and, therefore, the concentration of consumption of the residences in a single peak time should be avoided. It should also be noted that the periods that comprise considerable consumption values comply with the range of use constraints imposed by the consumer, so that planning is performed considering not only the tariff values, but also the routine and preferences of the residents.

In turn, the optimized consumption planning for the whole group, obtained for the same planning horizon, can be observed in Fig. 4. In this figure, the upper bar graph indicates the total power consumption at each of the planning horizon hours. The lower graph of lines shows the hourly rates that were notified to the consumer.

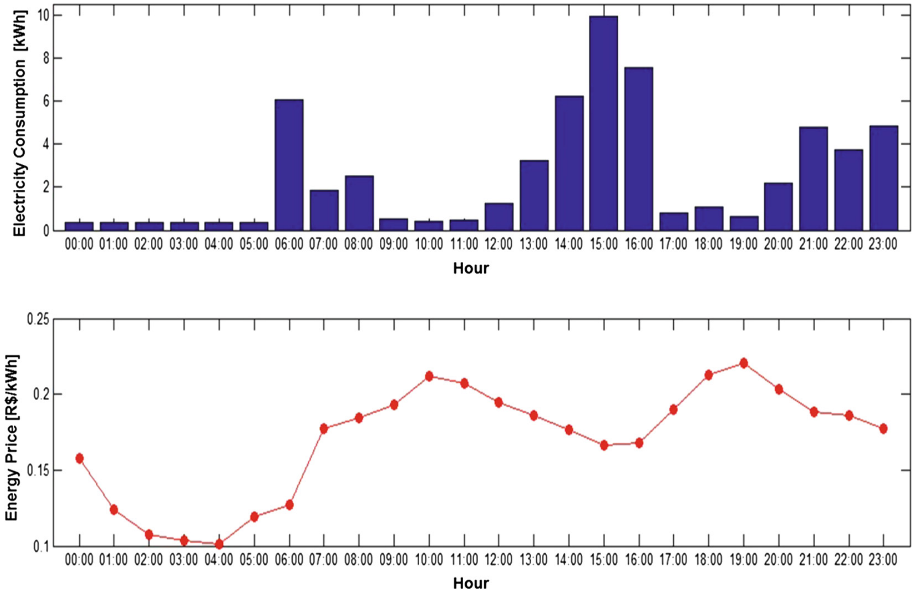

Fig. 4. Optimized planning of consumption for the group of consumers.

As shown in Fig. 4, the optimized planning of consumption for the group of consumers has a more uniform distribution than the individual plans analyzed in Fig. 3. This characteristic is consonant with the goal of minimizing PAR, since the uniformity of the distribution of consumption over the planning horizon results in a decrease in consumption at peak times. It is noted that the consumption trend observed in the optimized planning has a strong relation to the hourly values of the tariff. In this way, the schedules with the highest consumption concentration are precisely the feasible schedules (which respect the constraints imposed by the consumer) in which the value of the tariff presents a decrease. According to this trend, the peak consumption hour is at 3:00 p.m., coinciding exactly with the time at which the tariff presents its minimum value among the feasible schedules.

Based on the results analyzed, it is possible to affirm that the result obtained by applying the GSA to the demand response optimization model proposed in [6] was shown to be duly consistent with the variation of the tariffs paid for the energy consumption and with the reduction of consumption peaks through the minimization of PAR.

6 Conclusions

This paper presents an application of GSA to solve the demand response problem for residential consumers that use Real-Time Pricing. In this tariff structure, the energy price varies in short intervals of time and the consumer is usually notified about the prices on a daily or hourly basis. Due to the greater discretization of prices, Real-Time Pricing tariffs are the ones that best reproduce the volatility of energy prices. For this reason, this kind of tariff structure is generally considered to be very complex.

From the results obtained it was possible to note that the GSA proved to be a meta-heuristic with great potential for the proposed application. Optimized consumption schedules obtained through the application of the GSA in the optimization model proposed by [6] were able to minimize the energy price for a group of residential consumers. Moreover, the model still respects the comfort of the residents and minimizes peak demands. Finally, the main contribution of this paper is the formulation of the optimized consumption scheduling problem and then the specific study of the obtained results, aiming the demand response.

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