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Demand Response Driven by Distribution Network Voltage Limit Violation: A Genetic Algorithm Approach for Load Shifting

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ABSTRACT The residential sector electricity demand has been increasing over the years, leading to an increasing effort of the power network components, namely during the peak demand periods. This demand increasing together with the increasing levels of renewable-based energy generation and the need to ensure the electricity service quality, namely in terms of the voltage profile, is challenging the distribution network operation. Demand response can play an important role in facing these challenges, bringing several benefits, both for the network operation and for the consumer (e.g., increase network components lifetime and consumers bill reduction). The present research work proposes a genetic algorithm-based model to use the consumers' load flexibility with demand response event participation. The proposed method optimally shifts residential loads to enable the consumers' participation in demand response while respecting consumers' preferences and constraints. A realistic low voltage distribution network with 236 buses is used to illustrate the application of the proposed model. The results show considerable energy cost savings for consumers and an improvement in voltage profile.

INDEX TERMS Demand response, distribution network, load flexibility, load shifting, voltage profile improvement.

NOMENCLATURE

API	Application programming interface.
BFA	Bacterial foraging.
DR	Demand response.
DSM	Demand-side management.
DSO	Distribution system operator.
GA	Genetic algorithm.
HTTP	Hypertext transfer protocol.
IoT	Internet of things.
JSON	JavaScript object notation.
PV	Photovoltaic.
RES	Renewable energy sources.
REST	Representational state transfer.
$EnPay$	Energy cost (€/kWh).
t	Time frame.
ti	Initial time frame.
tf	Final time frame.
m	Shiftable appliance index.
M	Maximum number of available shiftable appliances.
E_{task}	Energy consumption (kWh).
E_{Gen}	Locally generated energy (kWh).
F	Fitness function.
T	Time window of the schedule.
E_{Price}	Energy price in a given time frame.
Ind^{1}_{chance}	Chances of individual 1 winning the tournament.
fit_1	Fitness of individual 1.
fit_2	Fitness of individual 2.

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I. INTRODUCTION

Nowadays, modern societies are highly dependent on electricity to ensure safe, reliable, and comfortable living. The electricity demand is expected to still increase in the future and is an essential requirement for economic development [1]–[3]. Over the past few years, the electrical energy sources' portfolio has been changing, contributing to renewable energy sources (RES) penetration growth. The large-scale integration of RES and the interest in placing the citizens as core players in future power systems play a crucial role in the efforts to reduce greenhouse gas emissions. Furthermore, the citizens' participation role is an important key to the success of smart grids [4], [5]. Taking advantage of the citizens' demand flexibility can facilitate and increase the use of local RES and enable their participation in demand response (DR) programs [6], [7]. DR can be seen as a response by consumers to a set of stimulus, such as the variation in the energy price or the payment of incentives to consumers who participate in DR events [8]–[10]. DR can be implemented by developing time of use energy pricing schemes that incentivize customers to shift all or part of their demand from peak to lower load periods [11]. Thus, the load shape change obtained will contribute to the reliability and power quality improvement as well as a total system cost reduction. In this way, generation planning and scheduling efficiency can also be improved [12].

A. LITERATURE REVIEW

Shiftable loads have recently received a great deal of attention due to their role in DR and peak load shaving programs [13]. The use of computational algorithms to solve load demand planning and optimization problems, namely concerning load shifting, leads to potential monetary and energy savings when confronted with DR events. Promising results by using DR were obtained for different applications, as shown in [14].

In what concerns load shifting, [15] presented a quantitative estimate of the possible reduction in network power losses when domestic energy demand is shifted over time. However, this research is focused on the network perspective and does not consider the consumers' benefits or the local generation. Reference [16] introduced an analysis of load shifting performed in São Miguel Island, Azores, indicating that through defined rules of load shifting, the baseload limit can be elevated, and the limits for the maximum installed RES capacity can be set. Nevertheless, in [16], the benefits for consumers participating in load shifting are neglected as well as the network operation parameters (e.g., voltage profile). Pourmousavi *et al.* [17] assessed the thermostat setpoint control of aggregate electric water heaters for load shifting to provide the desired balancing reserve for the utility. This research work aims only at the thermostat setpoint control of aggregate electric water heaters, ignoring other appliances and the network operation analysis. A variety of approaches are used to solve the load shifting problem, such as particle swarm optimization-based algorithms [18], reinforcement learning [19], ant lion optimization algorithm [20], linear programming [21], and cuckoo search with grasshopper optimization algorithms [22]. The genetic algorithm (GA) is also considered in several works to solve the load shifting problem [23]–[25]. In [23], a demand-side management (DSM) approach with GA is used to give the best solution based on optimizing the load shaping in DSM. Awais *et al.* [24] proposed a similar approach, but with a greater focus on minimizing the peak to average ratio and the overall electricity consumption cost. Reference [25] adapted a hybridization of two optimization approaches, bacterial foraging (BFA) and GA, to reach the best solution. However, these research works have significant limitations, including neglecting the influence of load shifting and local generation on network operation [18], [19], [21]–[25], different appliances [19]–[21], and consumers gain from participating in the load shifting [23], [25]. Moreover, in [26], Bashir *et al.* used several machine learning algorithms, such as support vector machines, K-nearest neighbor, logistic regression, naive bayes, neural networks, and decision tree classifier, to predict the smart grid stability. A summary of the surveyed literature can be found in Table 1.

B. CONTRIBUTIONS

To our best knowledge, the above-cited literature presents several limitations in what concerns the load flexibility in the DR event participation (load shifting) field. To fill those gaps, this research work presents the following key contributions:

- Using the load flexibility from different shiftable appliances with demand response participation, managed by an energy resource aggregator;
- Minimize the energy costs considering in the proposed model the real-time energy price and the locally generated energy;
- Considering the consumers benefit from participating in the load shifting;
- Improve the service quality, namely in terms of voltage magnitude profile.

A GA based-model has been used for demand response participation modeling. GA was chosen once it offers high flexibility for modeling the problem, and is a well-studied and reliable metaheuristic search-based optimization algorithm that provides semi-consistent good solutions, and is highly adaptable due to its optimized control parameters (e.g., population size, mutation probability, and execution time) [27], [28]. Also, it is worthy to note that the GA is widely used for other kinds of complex problems, such as in problems related to heart disease diagnostic [29], internet of things (IoT) related problems [30], and tuning other optimization algorithms [31].

To demonstrate the application of the proposed model, twenty consumers of a realistic 400V low voltage distribution network with 236 buses and a total of 96 loads (residences) were used.

TABLE 1. Literature surveyed summarized.

Ref.	Topic	Technique	Contribution / Outcome
[13]	Optimal demand bidding for a time-shiftable load	Multistage stochastic optimization	Optimal price and energy bids to day-ahead market and energy bids to real-time market to operate time-shiftable loads with deadlines
[14]	Minimization of energy costs considering the scheduling of tasks, local renewable energy sources, and multiple energy retailers	Genetic algorithm	Integration of demand response events in the real-time update of the production schedule to minimize the operation costs of a production line
[15]	Spreadsheet model to quantify the effect of profile shape on distribution losses	Quantitative estimation	Reduction in power losses by shifting in time the domestic energy demand
[16]	Defined rules for load shifting to check the limits for the maximum installed capacity	Rules-based	Load shifting with significant impact on São Miguel Island (Azores) demand profile, with demand peaks reduced and off-peaks filled
[17]	Thermostat setpoint control of aggregated electric water heaters	Control-based	Economic benefits to the customers while maintaining their comfort level and providing a large percentage of desired balancing reserve in the presence of wind generation
[18]	Demand side management based on day-ahead load shifting	Modified particle swarm optimization	Obtained a reduction in the peak load demand and overall operation cost
[19]	Combination of two reinforcement learning for load shifting in a cooling supply system	Deep Q-network and deep deterministic policy gradient	Investigated algorithms from the field of reinforcement learning for model-free load shifting in a cooling network leading to an average of 14% savings in operation cost
[20]	Energy management of a hybrid renewable energy to meet the energy demand using load shifting	Hybrid galactic–swarm optimization and ant–lion optimization algorithm	Shifting the load during peak hours by matching the energy generation and load demand providing to consumer savings of 24% and peak reduction of 25% and 80%
[21]	Instantaneous load shifting for industrial and commercial buildings	Linear optimization and nonlinear regression	The results reveal that consumers' electricity bills have decreased while maintaining required comfort levels. The real-time pricing load synchronization problem is also addressed in the results
[22]	Scheduling machines according to the day-ahead pricing signal	Grasshopper optimization algorithm and cuckoo search optimization algorithm	Results show that the consumed energy price is minimized by shifting some load to low-demand load hours without disturbing its operation
[23]	Demand side management for load redistribution in industry	Genetic algorithm	Obtained an overall reduction of power utilization of 21.91% during the peak hours
[24]	Minimization of the peak average ratio and the overall electricity consumption	Genetic algorithm	The model leads to a minimization of the electricity bill by proper load shifting as well as the peak load demand
[25]	Cost minimization by load shifting	Bacterial foraging and genetic algorithm	Obtained a reduction of the total cost and peak average ratio by shifting the load on off-peak hours with very little difference between minimum and maximum 95% confidence interval
[26]	Stability prediction of smart grid using machine learning algorithms	Support vector machines, K-nearest neighbor, logistic regression, naive bayes, neural networks, and decision tree classifier	Achieved that the decision tree classification algorithm outperforms the other algorithms in smart grid stability prediction

C. PAPER ORGANIZATION

This paper is divided into five main sections. After this first introductory section, section II describes the proposed methodology for load shifting and integration with the GA. Section III will present the case study with real data. Section IV will show the discussion of the results. Finally, the main conclusions are presented in section V.

II. PROPOSED METHODOLOGY

This section presents the methodology adopted in this research work. Subsection II-A shows details about the approach for load flexibility with demand response participation. Subsection II-B presents the load shifting model implementation architecture.

A. LOAD SHIFTING MODEL

Managing the flexibility provided by the active consumers in a distribution grid is a complex task. Thus, the aggregator requires proper methods and tools to deal with that complexity. Figure 1 presents the diagram of the proposed methodology for load shifting.

The model is able to use the forecast data for the day ahead, i.e., load demand, photovoltaic (PV) generation, and electric energy price, to perform the demand response participation (managed by an energy resources aggregator). For the study purpose and to show the advantage of the model, the authors are using a collection of data consumption from residences and photovoltaic PV generation. The data consumption collection was obtained in REFIT: Electrical Load

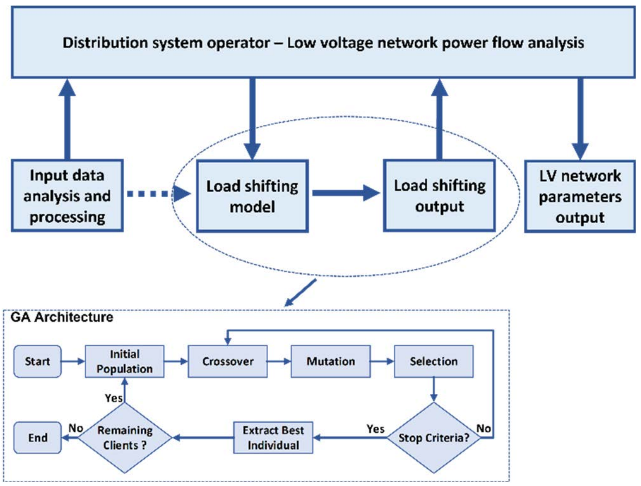

FIGURE 1. Proposed load shifting model diagram.

Measurements Dataset [32]. This dataset includes the whole residence aggregate loads and nine individual appliance measurements at 8-second intervals per residence, collected continuously over two years from 20 residences. The data collection was obtained from the collected measures of the PV panels installed in the GECAD[1] laboratory research center in what concerns the PV generation. The quality of the forecast data is analyzed to detect possible data errors.

The authors deal with a heavy database of data consumption and PV generation for the paper's purpose. In this way, the block input data and processing are important to filter possible data errors and select the data to be used for the study. For data selection, it was chosen one day (15 minutes time resolution, i.e., 96 periods) where the consumption measures were recorded in all considered equipment (dishwasher, washing machine, dryer). The aggregator supplies the genetic algorithm (with a detailed explanation in the Genetic Algorithm for Load Shifting subsection) - Load shifting model block and also provides the distribution system operator (DSO) - Distribution system operator – Low voltage network power flow analysis block - with demand and generation forecast values (as it said before, for the study propose the authors are using a collection of data consumption from residences and PV generation). With that, the DSO performs initiatives to detect bus voltage violations (power flow analysis). A load reduction request in the periods and bus where it is verified the voltage violation is sent to the aggregator (Load shifting model block), and a DR event (load shifting) is triggered. Next, the aggregator sends (Load shifting output block) to DSO the new demand values (after load shifting) for new power flow analyses. The block LV network parameters outputs present the results obtained by the power flow analyses, namely the new voltage profiles, power losses, and the power flow.

[1] Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (https://www.gecad.isep.ipp.pt/GECAD/Pages/Presentation/Home.aspx)

1) GENETIC ALGORITHM FOR LOAD SHIFTING

GAs were proposed by Holland [33] and are based on the discoveries made by Charles Darwin and his Theory of the Evolution of Species. GAs are global optimization algorithms based on natural selection and genetic mechanisms. They employ a parallel and structured but random search strategy geared towards strengthening the search for "high aptitude" points. Although random, they do not correspond to random, nontargeted searches, as they explore historical information to find new search points where better performance is expected. This is done through iterative processes, where each iteration is called a generation. The model for the development of the GA is, at first, implemented in Python by a REST API service that receives and sends HTTP requests of JSON files through the POST method. This API serves as an intermediary for communication between requesters and the GA. The proposed solution uses the notion of periods (time frames) without really understanding what they represent (e.g., five seconds, ten minutes, or one hour), leaving this definition to the user. Therefore, all input data must follow the same notion of periods. For example, suppose the length of a task is specified in a one-minute period. In that case, the prices and forecasts of the energy market must also be provided in a one-minute period, ensuring data consistency. Energy units must be specified as Wh, but their unit prefix (e.g., kWh or MWh) can differ. Using the same logic as periods, the user must apply the same prefix to all energy units. The domain of the GA is characterized by a set of concepts that allow load shifting, considering load flexibility with demand response participation and energy cost minimization. The proposed solution domain model, represented in Figure 2, can be divided into six fundamental concepts [14]:

- **Task.** A task represents an activity to be done in a shiftable appliance (e.g., washing clothes);
- **Shiftable Appliance.** A shiftable appliance describes a piece of equipment (e.g., dishwasher, air conditioner, tumble dryer) with controllable loads that can be shifted. It has a list of compatible tasks;
- **Client.** This concept portrays the association between different loads and a client;
- **Energy source.** An energy source describes a culmination of availability and price. It allows multiple energy providers (e.g., aggregator or retailer) and local generation (e.g., photovoltaic);
- **Demand response.** Portrays a demand response event that must be complied;
- **Constraint.** A constraint is a requirement that the algorithm must comply with (e.g., clothes can only be dried after washing).

The use of constraints is not necessary however, there are practical scenarios where physical constraints are in place and need to be portrayed. For the time being, the proposed solution has the following constraints[2]:

[2] The reader can find the detailed information about these constraints in [14].

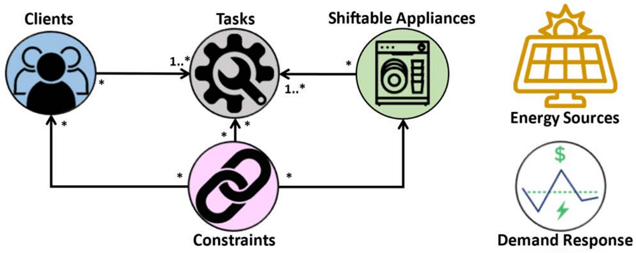

FIGURE 2. Domain model of the proposed methodology.

1) Task collision;
2) Task order;
3) Load task order;
4) Task setup;
5) Time leap;
6) Interruptible task;
7) Available appliance frames;
8) Load request deadline;
9) Load request task period range;
10) Energy limit;
11) Shift margin.

The energy limit constraint is crucial in this research work since it is used to stimulate participation in a demand response event. This constraint defines a limit of energy from energy sources with a tariff within a given interval of periods. Also, it can have monetary compensation for complying with the energy limit. The proposed GA model presents the following outputs information:

- The final cost;
- The energy consumed per energy source and cost in each period;
- The energy consumed per shiftable appliance and per period;
- The cost of each generation of the GA.

B. LOAD SHIFTING MODEL IMPLEMENTATION

The implementation of the GA model for the load shifting approach can be divided into five main phases: *i*) initial population, characterized by creating random work plans of the load (i.e., individuals); *ii*) crossover, for the spread of genes between individuals; *iii*) mutation, to insert diversity into the population in order to reduce the probability of getting stuck in a local optimum; *iv*) selection, to choose the individuals to inherit to the next population; *v*) finally, the extraction of the best individual from the last population created is done. Figure 3 represents the flowchart of the GA for load shifting energy cost optimization.

The proposed solution was developed in the Python programming language without any library related to GAs since no library can solve the complexity of the problem described in this research work.

1) INITIAL POPULATION

The GA begins by creating an initial random population that complies with all imposed constraints. Therefore, the GA always works with valid schedules. When creating each individual for the population, the algorithm prioritizes tasks with a smaller number of compatible shiftable appliances to decrease the rate of invalid schedules. Then, with the list of tasks associated with each shiftable appliance, the algorithm constructs a two-dimensional matrix that represents the work plan of the load. The matrix, shown as an example in Figure 4, defines the plan of a shiftable appliance and its working period. For example, in Figure 4, "Appliance 1" and "Appliance 2" could describe two different available washing machines, "Washing machine 1" and "Washing machine 2", respectively. Furthermore, tasks "T1", "T2", and "T5" could represent tasks with different washing programs that have different durations and energy consumption, for instance, turbo mode for "T1", normal mode for "T2", and eco mode for "T5". In addition, "Appliance 3" could be described as a tumble dryer, with tasks "T4" and "T3" representing tasks with slow dry mode and fast dry mode, respectively.

If an individual matrix is created with at least one constraint that is not complied with, the algorithm attempts to repair the individual by shifting tasks left or right or swapping tasks. However, if the repair is not successful, another individual is generated.

An energy limit constraint must be imposed for a load flexibility approach with demand response participation. In this case, the algorithm checks, for each individual created, if the given energy limit constraint interval, i.e., in the time frame interval of the demand response event, the energy usage from energy sources with prices above zero does not surpass the energy limit imposed by the demand response event. The energy usage from energy sources with price can be calculated through the following equation (1):

$$EnPay = \sum_{t=ti}^{tf}\left(\left(\sum_{m=1}^{M} E_{task}(t,m)\right) - E_{Gen}(t)\right) \tag{1}$$

where t represents a time frame (period), ti the initial time frame of the interval, tf the final time frame of the interval,

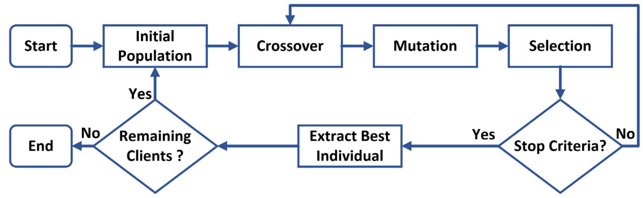

FIGURE 3. Flowchart of the GA for load shifting energy cost optimization.

Shiftable Appliance/Period	1	2	3	4	5
Appliance 1	T1		T5	T5	T5
Appliance 2				T2	T2
Appliance 3	T4	T4	T4		T3

FIGURE 4. Example of a GA individual, representing the matrix (appliance/period) where tasks are defined by their identifiers.

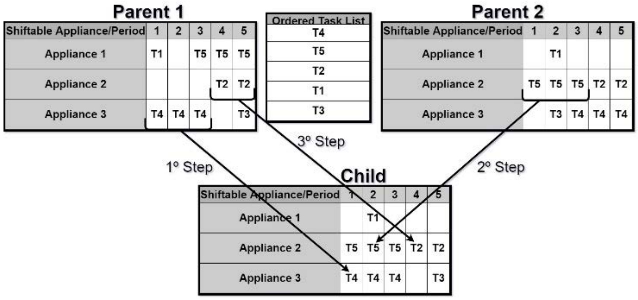

FIGURE 5. GA crossover example between two individuals, beginning in parent 1 with the 3 first steps shown.

m portrays a shiftable appliance index, and M the maximum number of available shiftable appliances. The energy consumption of a task in a given period is represented by E_{task}, and E_{Gen} defines the locally generated energy, which is energy free of charge (e.g., photovoltaic generation).

2) CROSSOVER

The crossover is made between two individuals randomly chosen that have not yet been crossed from the previous generation's population. The crossover adopted is characterized by being two-dimensional and following a more deterministic approach (i.e., balancing the tasks coming from each individual). The crossover between two parents (individuals) starts by organizing the list of tasks by decreasing the order of execution time. If they have equal times, it is ordered in ascending order of the number of shiftable appliances compatible, thus reducing the rate of invalid crossovers between two individuals. Then, in order of the task list created, two crossovers are done from the same list, each starting with a different parent. The first crossover begins by picking the first task and inserting in the child according to the parent 1 coordinates'; then it changes to parent 2, then parent 1 again, and follows this logic. Figure 5 represents an example of the first three steps in a crossover that starts with parent 1.

If the resulted child is not a valid schedule (i.e., it does not comply with all constraints), it is never added to the population pool.

3) MUTATION

The mutation procedure starts by determining which individuals from the population derived from the crossover will be mutated based on a percentage of mutation defined in the input data. If a mutation occurs on an individual, then a mutation of swapping two tasks is applied, therefore affecting task order of execution and/or appliance compatibility. If the resulted mutated individual does not comply with all constraints imposed, then the mutation is reversed, and another mutation, affecting different tasks in the schedule, is tried.

4) SELECTION

The selection begins with the unification of the crossed and mutated population with the population of the previous generation (i.e., the new and old populations, respectively). Then, any repetitions of individuals in the unified population are eliminated. Afterward, every individual is evaluated using the following fitness equation (2):

$$F = \frac{1}{\sum_{t=1}^{T}\left(\left(\left(\sum_{m=1}^{M} E_{task}(t, m)\right) - E_{Gen}(t)\right) \times E_{price}(t)\right)} \tag{2}$$

where t represents a time frame (period), T the time window of the schedule, m portrays a shiftable appliance index, and M the maximum number of shiftable appliances in the schedule. Both t and m are used to navigate in the schedule matrix (i.e., t represents the x cartesian coordinate and m the y coordinate). In a given time frame, the energy consumption of a task is represented by E_{task}, E_{Gen} portrays the locally generated energy (e.g., photovoltaic generation) available at a given time frame, and E_{Price} describes the energy price in a given time frame. In short, the energy cost is determined as a result of the respective energy price.

Then, after each individual is evaluated, the algorithm selects the n best individuals (i.e., elite selection) according to the remaining individuals (i.e., population size less n) are obtained from non-elite tournaments. The tournaments randomly select two individuals and make them compete based on their fitness scores, obtained through equation (2). The chances of individual 1 winning the tournament can be calculated using the following equation (3):

$$Ind_{chance}^{1} = \frac{fit_1}{fit_1 + fit_2} \tag{3}$$

where fit_1 and fit_2 represent the fitness of individual 1 and individual 2, respectively.

Then, the algorithm generates a random decimal number between 0 and 1. If the generated number is lower than the chance of individual 1 winning, equation (3), then individual 1 is declared the winner. If not, individual 2 wins. Therefore, the individual with the lowest cost (i.e., highest fitness) is most likely to be inherited by the next generation. In fact, this non-elite tournament approach aims to reduce even further the probability of the GA getting stuck in a local optimum since it does not necessarily inherit the individuals with the highest fitness values, thus giving lower fitness individuals a chance to inherit to the next generation.

5) EXTRACT BEST INDIVIDUAL

After the selection phase, a new generation begins with the population obtained from this selection, and all the procedures mentioned above are repeated. Since the GA always works with valid schedules, in our case, with energy limit constraints, the overall evolution of the GA always trends to create more schedules that comply with the demand response event. Also, having more valid schedules, it has more flexibility to reduce the overall energy costs at the same time. Finally, after at least one stop condition is met (e.g., execution time, number of generations, stagnation, or cost reached), the lowest cost individual (i.e., best individual), found by the

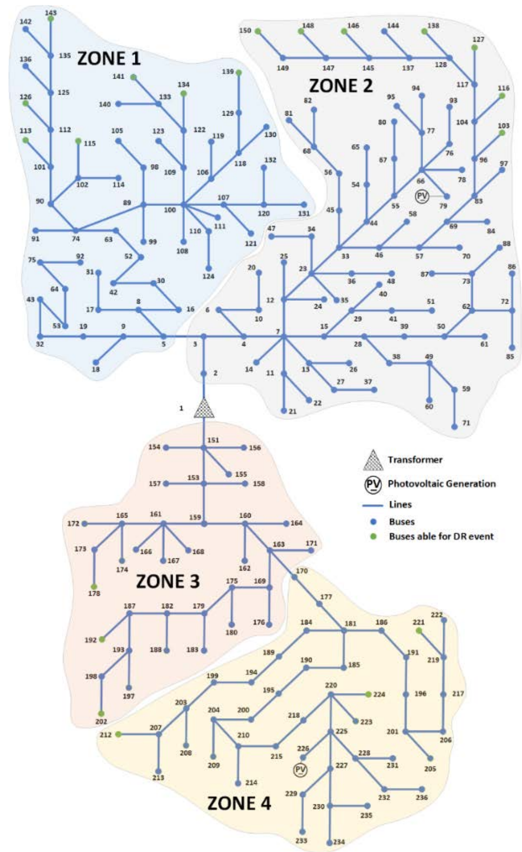

FIGURE 6. Single line low voltage distribution network.

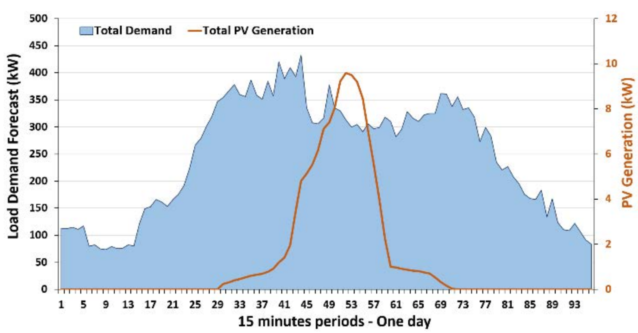

FIGURE 7. Day-ahead load demand and PV generation - 15 minutes periods (12AM to 11:45PM from 08/05/2014).

GA, is extracted from the last population created. Therefore, through equation (2), the GA tries to minimize the energy cost of the load by optimizing the schedule as much as possible, also taking into consideration constraints, such as task orders, task collisions, load deadlines, PV generation, etc., but mainly energy limit constraints.

III. CASE STUDY

The low voltage distribution network presented in Figure 6 illustrates the use of the proposed methodology. This network is based on a real distributed grid and has 236 buses and 235 underground cables. It is operated under a radial topology with a total installed power of 679.65 kVA. There are 96 residential consumers connected to this network, of which two have rooftop PV panels (7.5 kWp each). A 1000 kVA transformer carries out the network supply with 10 kV of the primary voltage and 420V in the transformer secondary.

For the study purpose, the consumers' data from REFIT [32] substitutes the data of 20 original consumers from the network (represented as green buses in Figure 6). Each of these selected consumers has several appliances with load flexibility, enabling their participation in DR events. The flexible appliances for the selected 20 consumers are presented in Table 2. The total day-ahead demand and PV generation are presented in Figure 7, considering periods of 15 minutes for day 08 of May of 2014. As shown in Figure 7, the peak demand is verified between periods 41 and 45, i.e., between 10:00AM and 11:00AM.

Regarding PV generation, the maximum generation is obtained between periods 51 and 55 (12:30PM – 01:30PM). Voltage magnitude violations are considered for voltage values lower than 0.95 p.u. and greater than 1.05 p.u.. The GA input optimization control parameters used for the case study are represented in Table 3.

TABLE 2. Selected bus/consumers and flexible appliances.

Bus/Consumers	Appliances
103, 113	Tumble dryer and dishwasher
115, 116	Tumble dryer
126, 127, 178	Tumble dryer
134, 138, 212	Dishwasher
139, 146, 192, 221	Dishwasher
141, 148	Washing machine
143, 150, 202, 224	Washing machine

TABLE 3. Selected genetic algorithm optimization control parameters.

Parameter	Value
Population size	15
Elite size	4
Mutation probability	5%
Execution time	1800 seconds

The electricity prices are taken from a double time of use tariff offered in Portugal to residential consumers and can be seen in Table 4. In addition, each customer who participates in the considered DR event receives compensation of 0.05 €/kWh of shifted demand (remuneration contract between customer and aggregator), which will be subtracted from the electricity bill.

IV. RESULTS AND DISCUSSION

The proposed methodology is applied to the case study presented in section III using a computer with one Intel Xeon E5-2620 v2 processor and 16 GB of RAM running Windows 10 Pro and using Python 3.8 through Visual Code IDE.[3] MATLAB R2018a 64 bits and a tool for electric

[3]https://code.visualstudio.com

TABLE 4. Time-of-use.

Day Period	Electricity Price (€/kWh)
12:00AM– 8:00AM 10:15PM – 11:45PM	0.1010
8:15AM – 10:00PM	0.1879

power system simulation and analysis - MATPOWER 7.0 [34] were used for network analysis studies. The used power flow method was the Newton Raphson since the considered network has a low R/X ratio.

Some works to solve a load shifting problem are presented in the literature, such as [18]–[25]. The authors tried to compare the run-time/time-consuming with [18]–[25] to show how the proposed model is efficient. Unfortunately, only one of them presents the model run-time / time-consuming, i.e., the reference [22]. In [22]it is shown a demand-side management strategy for the energy optimization problem for different load units in an industrial load. In this work, two bio-inspired optimization schemes (Grasshopper-Optimization Algorithm (GOA) and Cuckoo Search Optimization Algorithm (CSA)) are applied to load units for scheduling the automatic operated machines according to the day-ahead (24 periods – 1 hour period) pricing signal. The run-time for GOA is 8.702 seconds and for CSA is 9.152 seconds (we are assuming seconds because the [22] authors did not specify the time units in the paper).

Regarding the execution time, the proposed GA for load shifting took around 1800 seconds (30 minutes) for the 96 periods (one day – 15 minutes periods), i.e., an average of 19 seconds for each period. This execution time also includes the connection time with the network tool analysis. The network analysis execution time was 29 seconds for all periods (an average of 0.3 seconds for each 15 minutes periods). It is worthy to note that the 30 minutes mark represents a solid execution time compatible with the operation timeframe that guarantees a good result from the GA for the given case study. It is up to the user to configure the number of generations and/or the execution time of the GA. Such decisions will impact the quality of the result.

Considering the load demand presented in Figure 7, the DSO (after network analysis through power flow study) detects voltage lower limits violation, i.e., a value lower than 0.95 p.u. in bus 150, namely in periods 38 to 44, that correspond to the period from 9:30AM to 11:00AM (Figure 8). These periods correspond to peak load periods (which also includes the appliances working), and bus 150 is the one farthest from the transformer. So, these two situations together contribute to a considerable voltage drop in the referred bus. Thus, the DSO sends a load reduction request to the aggregator in ZONE 2 of the network.

In Figure 9, it can be seen the required load demand for the available appliances of each consumer selected by the aggregator to participate in the DR event. The selected consumers

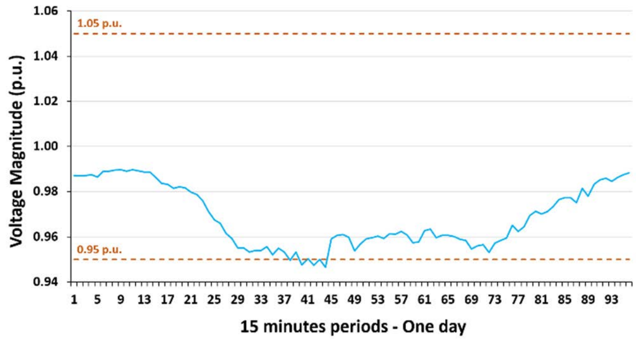

FIGURE 8. Voltage magnitude in bus 150 before DR event (12AM to 11:45PM from 08/05/2014).

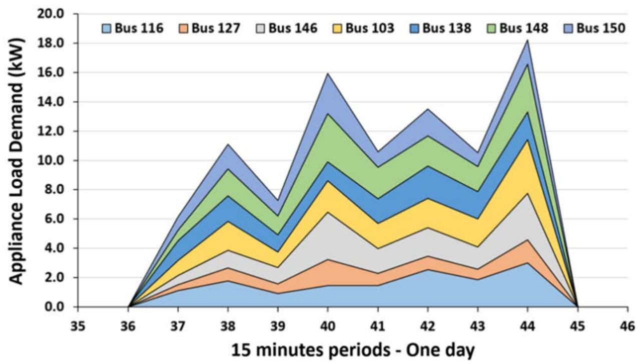

FIGURE 9. Load demand for participant appliances of each consumer before the DR event.

were the ones located on buses 103, 116, 127, 138, 146, 148, and 150.

Analyzing Figure 9, it is possible to see that the appliances (see Table 1) are working during the peak load periods, namely between periods 36 and 45, i.e., 08:45AM to 11:00AM (where the electricity prices are higher - see Table 2), contributing in this way for an increase in the current, causing a source capacity reduction and a voltage drop (violating the lower limit), as shown in Figure 8.

After running the proposed load shifting methodology (section II), the aggregator relocates the selected consumers' appliances' energy consumption in other periods, namely between periods 1 to 30 (12:00AM and 07:15AM), corresponding to off-peak periods. Comparing Figures 9 and 10, it is possible to see that the appliances are working more spread in time and not simultaneous. So, the appliances located in buses 103, 116, 138, and 118 are working mainly in the first 17 periods of the day (12:00AM – 04:00AM). The remaining ones (buses 127, 140, and 150) are working between periods 16 and 30 (03:45AM – 07:15AM). With this, it is possible to obtain savings for the consumers and, at the same time, mitigate the voltage profile issues, which proves the effectiveness of the proposed model.

Figure 11 shows the improvement of the voltage values in the periods where the voltage lower limit violations occurred before the DR event (periods 38 to 44 - 9:30AM to 11:00AM). A maximum of 0.4% improvement is verified

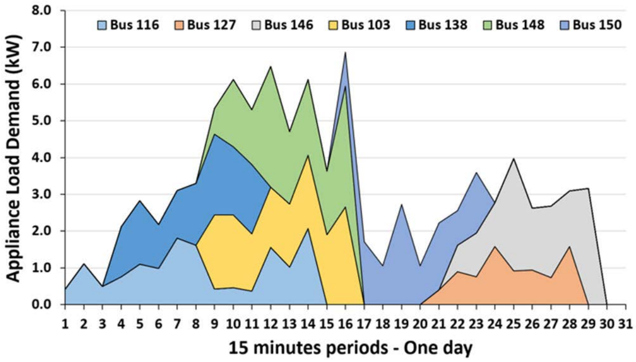

FIGURE 10. Load demand for participant appliances of each consumer after the DR event.

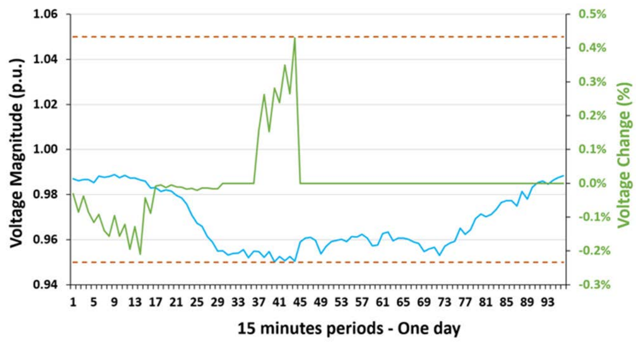

FIGURE 11. Voltage magnitude in bus 150 after DR event.

TABLE 5. Consumers costs comparison for the appliances operation.

Bus/ Consumers	Cost Before Load Shifting (€)	Cost After Load Shifting (€)	Cost After Load Shifting with Compensation (€)	Savings (€)	Savings (%)
116	0.666	0.358	0.181	0.485	72.85
127	0.366	0.197	0.107	0.259	70.85
146	0.680	0.365	0.184	0.495	72.86
103	0.723	0.391	0.197	0.529	72.86
138	0.621	0.334	0.168	0.452	72.86
148	0.767	0.412	0.208	0.559	72.86
150	0.558	0.300	0.151	0.407	72.87

in those periods contribution to the voltage magnitude being within the defined limits ($\geq$0.95 p.u. and $\leq$1.05 p.u.). This improvement in the voltage magnitude is related to shifting the appliances to other periods, namely off-peak periods, contributing to a current reduction in some peak periods (periods 36 and 45). Indeed, there is a voltage magnitude drop in the first thirty periods of the day (the maximum drop is 0.2%), which results from the load demand increase in those periods due to the load shifting made as a response to the DR event. However, despite this drop, the voltage magnitude remained within limits in all periods. Also, it is possible to see that the high voltage drop is verified in the first 17 periods. This occurs because, in these periods, many appliances are working (five appliances).

Besides the advantages provided to the network operator (namely mitigating the voltage magnitude violations), the load shifting model also presents considerable advantages to the consumer (bill reduction). Table 5 presents the cost comparison before load shifting and after load shifting. It is possible to see that participation in the DR event brought consumers significant cost savings. All available consumers to participate in DR events present more than 70% savings for the appliance operation. It is worthy to note besides the savings by shifting the appliance operation to other periods (lower electricity tariff), the consumers also have the compensation for that shifting (0.05 €/kWh).

V. CONCLUSION

With the electricity demand increase, the distribution network can often present operational issues regarding the violation of voltage magnitude. Therefore, demand response can play an important role in reducing the demand during those periods providing benefits both for the network and for the consumers.

This research paper presents a model using load flexibility and consumers participation in demand response events. The model considers real-time energy pricing and local generation. The proposed load shifting improves the network voltage profile and reduces the consumers' energy cost.

The practical use of the proposed model was illustrated using a case study with a realistic low voltage distribution network. The results show the improvement in the network voltage magnitude, leading the voltage to be within its limits. This is done with a small cost to the DSO, corresponding to the consumers' remuneration for their participation in the demand response event. From the consumers' point of view, they not only are remunerated for their participation, but they are also profiting from lower energy costs due to shifting their loads to periods with lower energy prices.

Our proposed model took around 1800 seconds (30 minutes) as total run-time. But it is worthy to note that we are considering 20 loads, 96 periods for energy price, demand, and PV generation. Moreover, our model can consider a set of constraints and include an electric power system simulation and analysis. Also, it is important to refer to the strong savings (more than 70%) for the consumers who participate in the demand response event and the voltage violation removal. Furthermore, the 30-minute mark represents a solid execution time that guarantees a good result from the genetic algorithm. The effectiveness of our proposed model has been demonstrated through the experiments and presented results.

This approach improves the reliability and service quality and reduces and/or postpones the network reinforcements or expansion. Thus, reducing the number of periods in which the network is under stress may increase the lifetime of the network components.

The main limitations of the current methodology are: a) the proposed model only includes residential consumers; b) only the demand response participation of home appliances is included; c) only voltage magnitude profile improvement is considered; d) the importance of demand response at each node and at each time slot is not considered.

As future work, the authors will improve the proposed model to include other types of consumers, namely the industrial ones; demand response participation of electric vehicles; implement in the model the demand response participation to mitigate lines congestion issues and analyze the possible needs and associated costs for the network reinforcement/expansion.

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