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A multi-objective genetic approach to domestic load scheduling in an energy management system

Ana Soares [a, b, *], Carlos Henggeler Antunes [b, c], Carlos Oliveira [b], Álvaro Gomes [b, c]

[a] University of Coimbra, Polo II, 3030-290 Coimbra, Portugal
[b] INESC Coimbra, Rua Antero de Quental 199, 3000-033 Coimbra, Portugal
[c] Dept. of Electrical Engineering and Computers, University of Coimbra, Polo II, 3030-290 Coimbra, Portugal

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ABSTRACT

In this paper a multi-objective genetic algorithm is used to solve a multi-objective model to optimize the time allocation of domestic loads within a planning period of 36 h, in a smart grid context. The management of controllable domestic loads is aimed at minimizing the electricity bill and the end-user's dissatisfaction concerning two different aspects: the preferred time slots for load operation and the risk of interruption of the energy supply. The genetic algorithm is similar to the Elitist NSGA-II (Non-dominated Sorting Genetic Algorithm II), in which some changes have been introduced to adapt it to the physical characteristics of the load scheduling problem and improve usability of results. The mathematical model explicitly considers economical, technical, quality of service and comfort aspects. Illustrative results are presented and the characteristics of different solutions are analyzed.

1. Introduction

The concerns about the dependency of fossil fuels, which are mainly originated in politically unstable regions, as well as their scarcity and negative impact on the environment, have motivated the search for the diversification of energy sources. Renewables are seen in this context as an option to reduce this external energy dependency and, at the same time, to decrease the environmental burden associated with the use of fossil fuels [1]. Due to these reasons and the policies used to incentivize the deployment of distributed generation, renewables have increased their share in the energy mix [2–6]. However, the problems associated with the fluctuation of energy generation from renewable sources still has to be addressed in order to better integrate them in the supply system [6,7]. DR (Demand response) is a valuable tool that can be used to reshape the end-user's consumption profile according to the available generation, grid requests and consumer's preferences, while simultaneously helping to compensate for the volatility of output power in renewable energy sources [3,8].

Recently, the "smart grid" concept has gained widespread attention as an electric grid with the capability of two-way communication offering the end-users adequate signals, namely kWh price incentives, in order to motivate them to shape their demand profile and adequately react to the grid requirements [9]. While until a few years ago there was a clear separation between electricity producers and consumers, nowadays with the increase of local domestic distributed generation based on renewables this borderline has been smudged. Therefore, smart grids are also expected to facilitate a better integration of fluctuating renewable energy and local distributed generation [10,11], in addition to other features expectedly to be delivered by smart grids such as self-healing capabilities, ability to accommodate storage options, increase the efficient operation of electricity markets, improve power quality, and globally optimize assets [11–13]. Furthermore, particular attention is being paid to the introduction of new loads such as electric vehicles [14–16]. The envisioned utilization of PHEV (plug-in hybrid electric vehicles) is likely to strongly increase the average electricity demand per household causing additional pressure on the electric system concerning the volatility of demand and capacity of the infrastructure [14]. So, although the individual PHEV has a very slight impact on the system, the aggregation of a large number of PHEVs may significantly affect the aggregate consumption and system reliability [1].

With the adequate technology, information and incentives, end-users may engage in a more active role, namely by modifying their demand and energy purchasing patterns [17]. The active management of controllable loads, besides allowing re-shaping end-user's

* Corresponding author. University of Coimbra, Polo II, 3030-290 Coimbra, Portugal.
E-mail addresses: argsoares@gmail.com, argsoares@inescc.pt (A. Soares).

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consumption patterns and lowering their electricity bills may also strongly contribute to the deployment of local renewable generation in power systems. Price signals reflecting real operational costs of generation and network instead of a flat rate are likely to induce consumers to react and change their consumption patterns to achieve savings in the monthly electricity bill. Since consumers are self-interested and autonomous agents, but lack the required knowledge and time to optimize electricity consumption given the multiplicity of decision parameters and constraints involved plus their possible variation over time [18], EMS (energy management systems) can be the solution to "automate" that change. EMS endowed with adequate optimization algorithms are a valuable tool to derive economic savings, maximize the quality of energy services and globally optimize the use of all energy resources [19].

Despite residential consumers' individual demand is relatively small when compared to the demand of other type of consumers, their aggregate demand is very significant [20,21]. In addition, some domestic end-use loads have characteristics that allow them to be managed without decreasing the quality of the energy service provided [18,20]. Although until recently these consumers were not motivated to change their demand pattern, except when billed under a dual-tariff, which did not require a big effort to schedule load, this is likely to change in the near future mainly due to the deployment of advanced metering infrastructure and the introduction of dynamic tariffs [22,23]. These dynamic tariffs should be designed in such a way that, when used together with consumption feedback, contribute to educate and encourage consumers to redistribute or reduce peak demand [24]. However, this redistribution of demand may differ according to the perspective. I.e., while for the system the main goal might be reducing power peaks and grid congestion, for the domestic end-user the goals are simultaneously reducing the electricity bill and the possible dissatisfaction associated with load management.

Domestic EMS can be used in this context to make the best decisions when scheduling the loads to be managed according to input signals and the end-user's preferences. These preferences may include time slots for load operation and risk aversion associated with the interruption of supply due to unexpected variations of the non-controllable base load. The reduction of the electricity bill and the reduction of end-user's dissatisfaction are however two conflicting objectives thus leading to a multi-objective problem.

Recently, several studies focused on decision support tools to help domestic end-users optimizing different energy resources. The algorithm developed in Ref. [20] schedules the operation of home appliances, namely shiftable loads (dishwasher, laundry machine, and electric vehicle), controllable loads (lighting and heating, ventilation and air conditioning system), and a storage system. The strategy used includes an exponential smoothing model to predict power requested to the grid by the managed loads and Bayes theorem to compute the probability of using a given load based on previously gathered information. [25] presents an algorithm based on binary particle swarm optimization to schedule some interruptible loads over a 16 h period. Concerning thermostatically controlled loads, [26] depicts an appliance commitment algorithm for scheduling those loads based on price and consumption forecasts considering users' comfort settings to obtain the minimum payment or the maximum comfort. [27] addresses the problem from a different perspective and proposes a three-step control methodology to manage distributed generation, distributed storage and consumption, stating that objectives like peak shaving or forming a virtual power plant can be achieved without harming the comfort of residents.

The aim of our paper is then to solve a multi-objective problem concerning the time allocation of domestic load operation while minimizing the costs associated with energy purchase and end-users' dissatisfaction. Despite load scheduling is a topic explored by several authors, our approach proposes a distinct way to deal with the problem, namely the objective functions, the input preferences and constraints considered [28]. For example, the way consumer's preferences regarding the time periods for load operation are modeled allows the consideration of distinct preference levels for the allocation of the manageable loads throughout the planning period. In order to hedge against unexpected variations in the base load, an energy safety margin is used penalizing solutions with power requested too close to the contracted power.

The motivation and interest of the problem have been addressed in this introduction. The problem formulation including the mathematical model is presented in section 2. In section 3 we focus on multi-objective optimization and present the methodology used to solve the load management problem, the parameters of the GA (genetic algorithm) and the inputs used, displaying the working cycles of the loads to be managed, kWh prices and contracted power variation along the planning period. Illustrative results are presented in section 4 and conclusions are drawn in section 5.

2. Problem formulation

Many real-world decision problems involve multiple and often conflicting objectives that need to be tackled and therefore explicitly considered in mathematical models. Also, several constraints must be satisfied and decision variables are often of combinatorial nature leading to overwhelming problem complexity [29,30]. [31] provide a survey of modeling, control and optimization techniques for a specific physical process. Multi-objective optimization problems do not have, in general, a single solution but a set of solutions called non-dominated solutions or Pareto optimal solutions as a result of conflicting objective functions, i.e. feasible solutions for which no improvement in any objective can be done without compromising at least one of the other objective functions. In real-world decisions, the selection of one of the non-dominated solutions as the final outcome to the problem should involve some form of operationalizing the decision-maker's preferences. These preferences enable to discriminate within the non-dominated set and assess in a meaningful manner the trade-offs among objectives. Therefore, a final recommendation should be understood as a best compromise solution. However, a global knowledge of the non-dominated set may be useful for decision support purposes and therefore a thorough exploration of the search space should be carried out.

The aim of our approach is to help the end-user to make decisions concerning the allocation of the operation of loads to be managed in the planning period. These decisions should minimize the electricity bill and minimize end-users' dissatisfaction. This dissatisfaction has two components: one concerning the time slots in which the end-user is more uncomfortable with the allocation of each load and the other component associated with the risk of interruption of energy supply. Both components were considered in the proposed approach using a utility function to establish the penalties associated with not meeting the preferred time slots specified by the end-user for the operation of each load or being too close to the contracted power which increases the risk of supply interruption in case of unanticipated changes in the base (uncontrolled) load. For the penalties associated with the time slots for each load (h_{jt}) it is important to note that the degree of dissatisfaction is different for different loads, and even for the same load it may vary along the day. The dissatisfaction levels are displayed in Fig. 1. A zero penalty corresponds to the timeframe in the planning period where the end-user clearly prefers the allocation of a given load. The preferences associated with the different time slots for the functioning of loads are based on the

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