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Design of an autonomous intelligent Demand-Side Management system using stochastic optimisation evolutionary algorithms

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ABSTRACT

Demand-Side Management systems aim to modulate energy consumption at the customer side of the meter using price incentives. Current incentive schemes allow consumers to reduce their costs, and from the point of view of the supplier play a role in load balancing, but do not lead to optimal demand patterns. In the context of charging fleets of electric vehicles, we propose a centralised method for setting overnight charging schedules. This method uses evolutionary algorithms to automatically search for optimal plans, representing both the charging schedule and the energy drawn from the grid at each time-step. In successive experiments, we optimise for increased state of charge, reduced peak demand, and reduced consumer costs. In simulations, the centralised method achieves improvements in performance relative to simple models of non-centralised consumer behaviour.

1. Introduction

EU policy aims to reduce greenhouse gas emissions and reduce dependency on imported fossil fuels. The "20–20–20" targets [1] mandate the reduction in member states to 20% below the 1990 emission levels, the supply of 20% of all energy from renewable energy sources (RESs) and a reduction in energy consumption by 20% by the year 2020.

Electric vehicles (EVs) are viewed as playing a role in reducing emissions in the transport sector, but their usage causes an increase in electricity demand. The use of RESs also causes problems for the efficient operation of a power plant [2]. Increased cycling (starting up and shutting down) of the power system results in increased wear and tear on the plant and can cause an increase of greenhouse gas emissions.

Therefore, new methods are required to increase electricity grid efficiency and reduce emissions. The smart grid (SG) is one main approach. A SG is a type of electrical power grid whose goal is to respond to the behaviour and actions of energy suppliers and consumers to efficiently deliver economic, reliable and sustainable electricity services. Multiple research areas have been explored in SG over recent years as a result of different challenges that have been posed to the electrical grid. One of the most explored areas in SG is Demand-Side Management (DSM) systems as shown by the increasing number of publications, ranging from the use of intelligent algorithms (e.g., game theory [3], Monte Carlo-based methods [4], evolutionary algorithms [5], multi-agent systems [6]), real-time systems [7], up to challenges and in-depth surveys on the area [8–11].

DSM is a set of measures to improve the energy system at the consumer side. DSM ranges from improving energy efficiency through the use of better insulation or better materials up to the use of autonomous systems to control energy resources [10]. DSM programs include different approaches, e.g., manual conservation and energy efficiency programs [12] and Residential Load Management (RLM) [6,3]). RLM programs based on smart pricing are amongst the most popular methods.

The motivation for smart grid tariff structures is twofold. They allow consumers to reduce their electricity costs. At the same time, the utility company achieves a reduction in the peak-to-average ratio (PAR) in load demand resulting from the shifted consumption [6]. If no special measures are taken to avoid them, high PAR values come about naturally because consumer electricity demand follows a diurnal pattern, with increased load in the morning, a dip in the afternoon, a rise in the evening, and a stronger dip in the middle of the night.

Some of these smart pricing methods are very popular. In particular, time-of-use (ToU) pricing has been widely adopted in some

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European countries [11]. Other smart pricing types include critical-peak pricing, extreme day pricing, and smart grid real-time pricing.

Motivated by smart price-based approaches, we are interested in developing an *autonomous intelligent* DSM system that shifts electricity consumption of electric vehicles (EVs). To this end, we use stochastic optimisation evolutionary algorithms (EAs). The main contribution of this work focuses on the notion of load shifting, borrowed from popular smart pricing-based methods. In contrast to typical DSM approaches such as dynamic pricing, which are based on an interaction between the utility and the user, we use a centralised approach, wherein the consumption schedule is set centrally based on complete information of all EVs. The motivation is to achieve improvements in performance. To do so, we use EAs to *automatically* generate (optimal) solutions. The use of all EVs is considered in the solution representation used in our EAs (described in detail in Section 2). We also use this in the evaluation of candidate solutions.

To test this idea, we considered a dynamic scenario of 28 simulated days, with the charging period from 18:00 to 07:30, divided into 28 time-slots of 30 min each. An action (switching EV charging on or off) can be taken at the beginning of each time-slot. We defined three different goals:

(a) that EVs' batteries are as fully charged as possible;
(b) we add an extra goal to (a) by aiming for a low fluctuation at the transformer load (i.e., low PAR); and finally,
(c) we add a third and final goal that aims to reduce electricity costs to the consumer by using a pricing signal based on ToU.

To achieve these three goals, we propose three fitness functions. Each will be used independently in our EA and will guide our evolutionary search to automatically create an (optimal) plan.

The core elements in this work are the following:

1. We study the impact of the representation and functions proposed in this work when scaling the problem up (i.e., from using a few EVs to using dozens of them) by measuring the transformer load, the initial and final state of charge (SoC), the PAR and electricity costs.
2. To do so, we used two EA approaches: a genetic algorithm and an evolution strategy and compared their performance against three non-intelligent approaches (i.e., Greedy, Midnight and Random methods), each of them simulating a specific user behaviour.
3. A dynamic scenario was used to study all these approaches by allowing having a variety of changes, i.e., different SoC for each EV for each of the simulated days, over a 28-day simulated period.

1.1. Importance of this research in DSM

DSM has been investigated extensively over recent years. For instance, it has been shown that more than 2000 scientific papers have been published in this area since the 1980s [4], with more than half in this decade. Fig. 1 shows a visual representation of the research trends followed in DSM (a) from 2010 until now, and (b) in 2014 only.[1]

As can be seen in Fig. 1 multiple topics have been covered in DSM, ranging from electricity costs, the use of electric vehicles, up to the use of data. The research conducted in this work lies at the very core of the research trend observed in this figure.

The challenges continuously presented to the grid, such as the aggregation of new electric devices (e.g., electric vehicles using the grid can double the average household load [3]) make the use of intelligent algorithms suitable to be used in the design/implementation of DSM systems. Fig. 1 shows this trend. For instance, notice the presence of "algorithms", "programs", and "methods". In fact, one could consider the presence of "algorithms" in the core of Fig. 1 if researchers had unified their use around this unique term instead of using various synonyms.

Several algorithms have been used in DSM system and each has focused their attention on different areas within DSM. For example, it has been shown that by adopting pricing tariffs which differentiate energy usage by time and level, a global optimal performance can be achieved by means of a Nash equilibrium of the formulated consumption scheduling game [3]. Multi-agent systems have also been used in DSM. For instance, the research conducted in [14] aimed to create a DSM based on these type of systems and studied different types of smart pricing, concluding that in all studied scenarios, a high PAR was observed under the use of these smart pricing models (e.g., ToU, critical peak price, real-time pricing).

In this work we use EAs to automatically create plans to intelligently charge EVs' batteries, aiming at reducing PAR, reducing load at the substation transformer, and reducing costs to the consumer.

This paper is organised as follows. In the following section we introduce our proposed approach. Section 3 shows the experimental setup used in this study. In Section 4, we present and discuss our findings. Section 5 draws some conclusions and presents some future work.

2. Proposed approach

2.1. Background

Evolutionary Algorithms (EAs) [15,16], also known as Evolutionary Computation systems, are influenced by the theory of evolution by natural selection. These algorithms have been with us for some decades and are very popular due to their successful application in a range of different problems, ranging from the automated design of an antenna carried out by NASA [17], the automated optimisation of game controllers [18,19], the automated design of combinational logic circuits [20,21], to automated optimal localisation for building seismic sensing stations [22]. EAs are "black-box", that is, they do not require any specific knowledge of the fitness function. They work even when, for example, it is not possible to define a gradient on the fitness function or to decompose the fitness function into a sum of per-variable objective functions. The fitness functions used in our work (described in Section 2.2) are not amenable to analytic solution or simple gradient-based optimisation, hence search algorithms such as EAs are required.

The idea behind EAs is to automatically generate (nearly) optimal solutions by "evolving" potential solutions (individuals forming a population) over time (generations) by using bio-inspired operators (e.g., crossover, mutation). More specifically, the evolutionary process includes the initialisation of the population $P(0)$ at generation $g=0$. The population consists of a number of individuals which represent potential solutions to the particular problem. At each iteration or generation (g), every individual within the population ($P(g)$) is evaluated using a *fitness function* that determines its fitness (i.e., how good or bad an individual is). Then, a selection mechanism takes place to stochastically pick the fittest individuals from the population. Some of the selected individuals are modified by genetic operators and the new

[1] Source: http://ieeexplore.ieee.org/Xplore/home.jsp. Last accessed date: 31/08/2014. Links of strength less than 55 (in (a)) or 20 (in (b)) are filtered out. Details on how this was produced can be found in [13].