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The optimization of demand response programs in smart grids

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HIGHLIGHTS

- An optimization model for the demand response program is made.
- TLBO and SFL algorithms are applied to reduce payment costs in smart grid.
- The optimal condition is provided for the maximization of the social welfare problem.
- An application to some residential houses located in the centre of Tehran city in Iran is demonstrated.

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ABSTRACT

The potential to schedule portion of the electricity demand in smart energy systems is clear as a significant opportunity to enhance the efficiency of the grids. Demand response is one of the new developments in the field of electricity which is meant to engage consumers in improving the energy consumption pattern. We used Teaching & Learning based Optimization (TLBO) and Shuffled Frog Leaping (SFL) algorithms to propose an optimization model for consumption scheduling in smart grid when payment costs of different periods are reduced. This study conducted on four types residential consumers obtained in the summer for some residential houses located in the centre of Tehran city in Iran: first with time of use pricing, second with real-time pricing, third one with critical peak pricing, and the last consumer had no tariff for pricing. The results demonstrate that the adoption of demand response programs can reduce total payment costs and determine a more efficient use of optimization techniques.

1. Introduction

Traditionally, power industry is based on centralized network where large power generation plants produce electricity that is used posterior at industrial or domestic level. This type of energy source chains necessitates power losses in transmission system due to the physical distance between the generation and consumption sites. Furthermore, the generation of electrical power in existing networks usually exploits non-renewable sources, which has a negative environmental impact. The fundamental objectives and challenges of managing energy systems are to reduce costs associated to the utilization of the electrical power network and to reduce the environmental impact and to comply the electrical energy demand subjected with unexpected disturbances. Smart grid is a solution to this challenge which has a huge benefit and efficiency (Strbac, 2008; FERC, 2006). For the consumer, this means they can intelligently manage their use to pay low cost in peak hours when energy prices are expensive. For environmental experts, this means using technology to help solve harmful climate changes, and avoid excessive carbon emissions, and for the officials of the power industry it means peak shaving, smart decision making, and providing accurate information on the status of the network. Smart electricity distribution networks are one of the newest technologies in the world, and are the resulting attempts of experts to modernize the distribution grids and enter into digital century (Wang et al., 2012; Joung and Kim, 2013; Siano, 2014). The main goal is to supply reliable electricity, and be responsive to the growing needs of customers with less damage to the environment. Smart metering system, smart display system, and smart controllers in these smart grids are for load-related issues (Koliou et al., 2015). By using smart metering system, the electrical energy consumption per consumer will be available at all times. Thus, unlike the traditional power network, consumers who do not use electricity in the hours when electricity prices are high will not be forced to pay additional fees for the power consumption of other consumers at these hours (Spees and Lave, 2007; Albadi and El-Saadany, 2008). Smart display system presents the up-to-date price of electricity to consumers. This technology, along with communication systems and smart metering systems, can improve demand response programs, because with being

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informed of electricity prices, consumers will save more on electricity use (Bartusch et al., 2011). In a smart grid, the responsibilities of actors in the value string of electric power derive in order to modify the integration of distributed renewable resources, energy-efficiency services, local balancing, smart energy systems and large volumes of information. Distribution system operators are at the heart of successfully performing changes at the consumer level all while warranting to customers a high level of reliability and quality of service via optimal planning (Koliou et al., 2015). The most important difference between smart grid and deregulated power systems that transmitting information, bilateral communication and make decision by networks for providing of their demand scan is performed in an intelligent manner. Since the electricity company can manage the power of a customer according to the contract between. That will not be successful without a smart structure in sending and receiving information. The primary structures of deregulated power system without smart grid, we can only pricing electricity for different times but the necessary facilities for a variety of contracts between the customer and the power company had not provided (Sen et al., 2014).

Demand Response (DR) has become a widely investigated solution for warranting grid reliability and market efficiency (De Joode et al., 2009). The value of this possibility will change according to the type of service, emplacement in the network, availability the flexibility and the time so that the flexibility becomes operational in smart grid. Incentive-based DR programs compensate end users for participation for flexibility provision. Price-based DR programs consist of variable prices reflective of active hourly market and grid conditions inclusive of real-time pricing (RTP), time of use (TOU) and critical peak pricing (CPP) (Bartusch and Alvehag, 2014). For the Electric Company operator, using of network refers to consumption (electricity requisition), generation (electric power injection) and presumption (combined requisition and injection). Distribution network fees have three essential segments: (i) the primary network connection charge; (ii) the required level of network tariffs (use-of-system charge) for allowed income during the regulative period and; (iii) the desirable structure of network tariffs, i.e. network charges according to consumer categories, periods of grid use and the mobility of customers when considering distributed energy resources. The primary connection charge becomes serious when connecting own energy resources since it pertains to who bears the cost responsibility for externalities imposed to the grid (Koliou et al., 2015).

Physically, the DR program will enhance the security of supply and included flexibility in power markets will prompt efficiency and performance (Torriti et al., 2010). The DR programs enable consumers to actively take part in power markets and in the optimal utilization of the smart grid, which in turn gives them the chance to benefit from optimizing usage based on communicated price conditions. The DR program is of great interest as a flexibility supplier, but nevertheless has not been illustrated in order to evaluate the extremity of potential savings that can be obtained in the electricity value chain; distribution grid is one of these lacking districts (Albadi and El-Saadany, 2008).

There exist a number of literatures on the price based DR programs. Different DR programs were developed based on game theory (Mohsenian-Rad et al., 2010; Yang et al., 2016), stochastic optimization (Nadali et al., 2014; Nazari and Akbari Foroud, 2013), and dual decomposition method (Samadi et al., 2010; Chen et al., 2012; Zakariazadeh et al., 2014). Then, a distributed power control algorithm was proposed for DR with communication loss. The works mentioned above assumed that the price is adjusted according to a pricing technique for a definitive pricing function. Recently, a linear pricing function was developed to achieve the balance between supply and demand sides for smart grid and a constrained pricing technique was used to design a distributed DR program (Neves et al., 2015; Ravindra and Iyer, 2014; Zehir and Bagriyanik, 2012). Nevertheless, few studies are devoted to the social optimality of the distributed electrical energy control under constrained pricing method and the influence of the disturbances on the control algorithms.

According to our findings, no stochastic electrical energy and reserve scheduling approach for a smart grid in which the demand side participation, as well as alternative nature of renewable generation sources, has been reported in the many papers. The fundamental focus of this study is, therefore, the proposal on a reserve scheduling approach including different types of DR programs in order to simplify the participation of multiple types of consumers in electrical energy and reserve scheduling. So, the theoretic contributions of this study are:

- The incentive and price based demand response program is formulated as a constrained power management system.
- Teaching & Learning based Optimization (TLBO) and Shuffled Frog Leaping (SFL) algorithms is proposed an optimization model for consumption scheduling in smart grid when payment costs of different periods are reduced.
- The optimal condition is provided for the equivalence of the equilibrium operating point of the grid and the minimum prices and payment costs of the different consumers is obtained.

2. Optimization methods

2.1. Teaching & learning based optimizing

Rao et al. (2011) was introduced the Teaching & Learning Based Optimizing (TLBO) algorithm to exploit the problem of optimal mechanical algorithm by considering the importance of a teacher on learners. The TLBO is a population-based algorithm like other natural-inspired algorithms Such as PSO and GA, where a group of learners is considered the population. The algorithm presents two fundamental methods of learning: teacher phase and learner phase. In this method, number of learners in a class is named class size and is shown by N, D is the number of courses proposed to the learners, and $MAXIT$ presents maximum number of iterations. The population X is randomly produced by a search space bounded. The jth parameter of the ith learner is determined values randomly using following equation (Rao et al., 2011a,b):

$$x^{0}_{(i,j)} = x^{\min}_{j} + rand \times (x^{\max}_{j} - x^{\min}_{j}) \tag{1}$$

where $rand$ is a uniformly distributed random variable within 0 and 1, $x^{\min}_{j}$ and $x^{\max}_{j}$ are the minimum and maximum value for jth parameter. The parameters of learner for the generation g are given by:

$$x^{g}_{(i)} = [x^{g}_{(i,1)}, x^{g}_{(i,2)}, x^{g}_{(i,3)}, \ldots , x^{g}_{(i,j)}, \ldots x^{g}_{(i,D)}] \tag{2}$$

Fig. 1 depicts the flowchart for this algorithm.

2.2. Shuffled Frog Leaping algorithm

The Shuffled Frog Leaping (SFL) algorithm is based on meta-heuristic developed by Eusuff and Lansey (2003) and was designed to seek a global solution by implementing an informed heuristic search space using a heuristic function (Eusuff et al., 2006). This algorithm is a combination of two genetic algorithm based on memetic algorithm and particle swarm optimization (PSO) algorithm. This algorithm is inspired by the life of a group of frogs when they are looking for food. The optimizer can exchange information between of local and global search elements. The SFL