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Two stage residential energy management under distribution locational marginal pricing

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ABSTRACT

This paper proposes a new optimization model for Smart Home Management Systems (SHMS) in order to increase the profits of Load Serve Entities (LSEs) and customers from technical and financial points of view. In the recent decades, performing Demand Response (DR) is one of the most efficient ways to improve the performance of power distribution systems in terms of power loss, and investment costs. The LSEs can implements some strategies like offering incentives to customers to change their consumption pattern with the aim of reducing power loss, improving asset management and increasing the profits. On the other hand, the end users can participate in DR programs to decrease electricity bills and earn monetary incentives from LSEs proportionate to their contributions to the energy loss reduction. In this paper, Distribution Locational Marginal Price (DLMP) instead of time-based pricing mechanism is applied to bill the customers. In the proposed strategy, the energy bill of customers and power loss of the system are simultaneously decreased. For dealing with uncertainties, stochastic variables computation module is designed which generates several scenarios by Monte Carlo simulation at each hour. The operation of household resources and appliances are optimized through a Mixed Integer Linear Programming (MILP), which has a two-stage stochastic model. The results explicitly show benefits of the proposed stochastic model since it provides accuracy in scheduling and decreases the operation cost. Besides, the superiority of DLMP and the proposed method over existing pricing mechanism is demonstrated.

1. Introduction

The energy efficiency is one of the main concerns of utilities, governments, investors, and other participants of the energy market in the recent two decades. Communication networks development, cutting-edge technologies, control devices, and distributed energy resources integration lead to fundamental changes in power system from the generation to end-users [1]. The utilities benefit from smart grid such as improved security, reduced peak loads, increased integration of renewables, and lower operational costs [2]. On the other hands, customers can reduce their electricity bills through scheduling smart appliances and energy resources via Smart Home Management System (SHMS). DR programs includes load shifting and peak shaving bring remarkable opportunities for LSEs and end users such as reduce the electricity bills, improve the asset management, and increase the utilization factors of power system devices like power lines and transformers [3,4]. The U.S. Department of Energy (DOE) has defined DR as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [5].

The residential consumers can reduce approximately 40% of energy consumption in the world by performing DR programs [6]. Therefore, electrical companies have been focusing on enabling technologies for DR activities in this sector [7,8]. The typical smart home may include different devices such as household appliances, Electric Vehicle (EV) with the capability of selling energy back to the grid (V2G) or injecting energy to home (V2H), distributed generation, solar panel, Energy Storage System (ESS), and etc. [9].

There have been several recent studies that investigated the optimal scheduling of smart home devices to maximize the profits of customers and LSEs. In Ref. [10], a neural network based scheduling of PV, ESS was proposed, but the price variability and power system conditions were neglected. In Ref. [11] the customers schedule home appliances for bill reduction at the community level, whereas aggregators minimize the energy purchasing expense from utilities at the market level. The aim of Ref. [12] was decreasing the electricity bills of consumers through establish-

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ing a day-ahead decentralized coordination method with appliance scheduling and energy sharing. Basit et al. proposed an autonomous energy management-based cost reduction solution for peak load times that was solved through a step-wise approach [13]. The aim of the optimization problem of Ref. [14] was to minimize the total cost to meet the electrical energy needs of the household in a dynamic pricing environment. In Ref. [15], a stochastic dynamic programming framework for the optimal energy management of a smart home in order to minimize electricity ratepayer cost, satisfy home power demand and PEV charging requirements is presented. In Ref. [16], the impact of price-based DR strategies on smart household load pattern variations was assessed. The novelty of the Ref. [17] was that the monthly bill target preferred by the consumer is achieved through the optimal operation of appliances over a multi-day time horizon. In some papers, the profits of retailers and aggregators have been taken into account. Besides, a different incentive based peak load reduction strategy is also considered in Ref. [18] for load reduction and voltage improvement. In Ref. [19], a new market mechanism is introduced for congestion management in distribution systems. In Ref. [20] the effect of households' appliances scheduling on the lifetime of a distribution transformer and energy bill of customers was assessed. In Ref. [21] a DLC based residential end-user coordination scheme is proposed in order to satisfy the distribution system operational limits. Paterakis et al. presented an optimal operation of a neighbourhood of smart households regarding minimizing the total energy procurement cost and preventing power peaks that are a harmful for distribution assets [22]. Amini et al. [23] proposed a systematic EV management for reducing power system loss. In Ref. [24] a smart home includes PV, ESS, and EV has been scheduled; however, the ability to inject power back to the house was neglected. In Ref. [25], customers' satisfaction oriented strategy for residential heating, ventilation, and air-conditioning (HVAC) units was proposed. The potential of HVAC offering load balancing services through bi-directional LSE signals for power reduction or increase requirements was analyzed in Ref. [26,27].

To surmount the shortcomings of the foregoing studies, this paper proposes a comprehensive methodology to optimize the profits of consumers and LSEs with respect to power loss, electricity bill, and asset management. Due to radial topology, higher electricity current, and resistance of distribution feeders, the power loss cannot be neglected. Therefore, a new pricing mechanism should be designed to represents energy price and power loss of distribution networks. To this end, DLMP is applied to handle the power loss and energy cost in distribution systems. This concept can provide a fair allocation of power loss among nodes and customers. Taking power loss of the network into account is the main difference between the LMP-based and DLMP based methodologies for smart home management. Since SHMS changes the loading of the distribution systems devices, this paper evaluates the impact of the proposed scheduling on asset management and lifetime of transformer. To the best knowledge of authors, this is the first study in the literature considering PV, EV with the capability of two-way energy trading through smart meters, a residential scale of ESS, and intelligent appliances in a single SHMS and distribution network in order to decrease energy bill and power loss simultaneously. In addition, the uncertainty of outdoor air temperature, PV, and uncontrollable loads are modelled by Monte Carlo simulation. The internal temperature of home and operation of appliances and energy resources are defined and modelled by two-stage stochastic optimization and solved by MILP.

This paper is organized as follows. Section 2 discusses the methodology of calculating loss allocation and DLMP. Afterward, Section 3 presents the smart home appliances and resources models. Section 4 provides the proposed method and objective function. The thermal model of a distribution transformer is presented in Section 5. In Section 6 the algorithm of the proposed method is discussed. Case study and numerical results are presented in Section 7. Finally, the conclusion is discussed in Section 8.

2. Distribution loss allocation methods

In a radial distribution system, electric power flows from a substation to end users. Energy loss allocation to each customer is related to load level, the location of the node, and equivalent impedance. In this paper, a practical method called the "Exact Method" is implemented to allocate active power loss to the nodes.

2.1. Exact method

The proposed approach uses the results of a converged load flow based on the identification of nodes and branches [28]. In a radial distribution system, branch current can be written as:

$$I(jj) = \sum_{k=1}^{N(jj)} \left[\frac{P\{ie(jj,k)\} + jQ\{ie(jj,k)\}}{V\{ie(jj,k)\}} \right]^* \tag{1}$$

where $I(jj)$ represents current of branch-jj, $N(jj)$ denotes total number of nodes beyond branch-jj, $ie(jj,k)$ represents nodes beyond branch-jj for $k = 1,2, \ldots, N(jj)$. In addition, P, Q, and V represent real power, reactive power, and voltage of nodes $ie(jj,k)$, respectively. Real power loss of branch-jj with sending end and receiving end voltages V_i and V_j is given by:

$$PLOSS\,(jj) = Re\{(V_i - V_j) * I(jj)\} \tag{2}$$

$$PLOSS(jj) = Re\left((V_i - V_j) * \sum_{k=1}^{N(jj)} \left[\frac{P\{ie(jj,k)\} + jQ\{ie(jj,k)\}}{V\{ie(jj,k)\}} \right]^* \right) \tag{3}$$

$$\left[\frac{V_i - V_j}{V\{ie(jj,k)\}} \right]^* = \alpha\{ie(jj,k)\} + j\beta\{ie(jj,k)\} \tag{4}$$

$$PLOSS(jj) = \sum_{k=1}^{N(jj)} \alpha\{ie(jj,k)\}P\{ie(jj,k)\} + \beta\{ie(jj,k)\}Q\{ie(jj,k)\} \tag{5}$$

where $PLOSS(jj)$ denotes real power loss of branch, $\alpha\{ie(jj,k)\}$ and $\beta\{ie(jj,k)\}$ represent real and imagine part of loss allocation factors for the consumer at node $ie(jj,k)$, respectively. Real power loss of branch jj allocated to customers connected to node $ie(jj,k)$ is given by

$$ploss\{jj, ie(jj,k)\} = \alpha\{ie(jj,k)\}P\{ie(jj,k)\} + \beta\{ie(jj,k)\}Q\{ie(jj,k)\} \tag{6}$$

The global value of losses to be supported by consumer connected to node l results from the sum of the losses allocated to it in each branch jj of the network is given (7):

$$Tplossi(l) = \sum_{jj=1}^{NB-1} ploss(jj,l) \quad for \ \ l = 2, 3, \ldots, NB. \tag{7}$$

2.2. Implementing DLMP in power distribution systems

The DLMP is similar to LMP in electricity wholesale market in which the cost of serving one additional unit of energy at a particular bus is displayed. DLMP of a node depends on load level, transmission LMP, circuit diagram, and allocated power loss which is given in Eq. (8)

$$DLMP_{i,t} = LMP_t\left(1 + \frac{Tploss_{i,t}}{PLOSS}\right) \tag{8}$$