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Model predictive control-based power dispatch for distribution system considering plug-in electric vehicle uncertainty

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ABSTRACT

As an important component of Smart Grid, advanced plug-in electric vehicles (PEVs) are drawing much more attention because of their high energy efficiency, low carbon and noise pollution, and low operational cost. Unlike other controllable loads, PEVs can be connected with the distribution system anytime and anywhere according to the customers' preference. The uncertain parameters (e.g., charging time, initial battery state-of-charge, start/end time) associated with PEV charging make it difficult to predict the charging load. Therefore, the inherent uncertainty and variability of the PEV charging load have complicated the operations of distribution systems. To address these challenges, this paper proposes a model predictive control (MPC)-based power dispatch approach. The proposed objective functions minimize the operational cost while accommodating the PEV charging uncertainty. Case studies are performed on a modified IEEE 37-bus test feeder. The numerical simulation results demonstrate the effectiveness and accuracy of the proposed MPC-based power dispatch scheme.

1. Introduction

Advanced PEVs are drawing much more attention because of their relatively higher energy efficiency, lower carbon and noise pollution, and higher fuel economy (Miles per Gallon of Gasoline Equivalent) [1]. The U.S. Department of Energy projects that about 1 million PEVs will be on the road by 2015 and 425,000 PEVs will be sold in 2015 alone. At this rate, plug-in vehicles would account for 2.5% of all new vehicle sales in 2015 [2]. Using a moderate market penetration scenario, the Electric Power Research Institute (EPRI) projects that 62% of the entire U.S. vehicle fleet will consist of PEVs by 2050 [3]. However, the increasing market penetration of those plug-in vehicles has significantly complicated the operations on the distribution system. Unlike any other controllable loads, these vehicles can be connected with a distribution system anywhere and anytime, bringing more spatial and temporal diversity and uncertainty [4]. As a result, the PEV charging load profile is highly uncertain and unpredictable. In last decade, a large number of literature [5–9] examined the impact of PEV charging load on power grids. They are based on a complete set of predefined data (e.g., when to charge and where to charge), which requires perfect forecasting PEV profiles over the entire energy scheduling horizon (e.g., next 24 h). Unfortunately, the perfect forecasting data is generally not available in real-world power system operations. Even a small PEV charging load forecasting error may result in great uncertainties for the real-time operation for a distribution system. To the best of the authors' knowledge, to date, the uncertainty issues of PEVs have not been well-discussed in any published literature work. Hence, a sophisticated power dispatch is highly needed to take these unique factors of PEVs into consideration.

MPC is an advanced method for process control, which has been widely used in a variety of industries demonstrating the promising results for the complex dynamic systems [10–12]. The focus on this paper is to apply MPC-based methods to achieve optimal power dispatch for distribution systems with high penetration of renewable energy resources and PEVs. The proposed MPC-based methods incorporate the uncertainty of PEV charging loads by combining the updated current PEV charging information (e.g., number of PEVs connected to charging stations, instant PEV battery state-of-charge (SOC), and battery capacity) with the short-term forecasting model. Although the uncertainty modeling of renewable energy output is not within the scope of this paper, the proposed MPC-based approach provides a framework to address a wide range of uncertainties and variability (e.g., renewable energy, and customer preference) for the power dispatch of distribution systems.

The major contributions of this paper include the following four aspects:

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1. Formulate power dispatch model for distribution systems in order to minimize the operational cost, the power losses, and the risk of energy transaction with the utility grid.
2. Propose a MPC-based on-line power dispatch method to accommodate the uncertainty and variability of the PEV charging load.
3. Investigate the PEV uncertainty under various charging schemes and operational conditions.
4. Evaluate the performance of a variety of power dispatch models at the distribution level considering the PEV uncertainty.

Section 2 proposes the problem formulation of the proposed power dispatch model. Section 3 introduces the MPC-based power dispatch methods and discusses the details on the solution algorithms as well as the simulation test platform. Section 4 introduces the case configuration of the proposed distribution test feeder and the simulation data. The numerical simulation results are presented in Section 4 also provides a detailed analysis and discussion on the proposed non-MPC and MPC-based power dispatch. Section 5 summarizes the paper's main findings and briefly discusses the future research trends.

2. Materials and methods

The successful deployment of the proposed energy and power dispatch model needs a reliable communication infrastructure in Smart Grid [13–15]. The smart meters and sensors can monitor the electric energy consumption at every single node of a power distribution system and exchange the real-time information with the control center through a reliable two-way communication network. The control center can also send back control signals to a variety of dispatchable load, distributed generators and energy storage devices. Since the proposed power dispatch scheme is dedicated to a power distribution system, the needed communication network infrastructure is related to field area network (FAN) and home area network (HAN) [16]. The detailed discussion on specific communication requirement for PEV charging applications can be found in [1]. Each electric vehicle is equipped with a two-way communication module. For example, dedicated short range communication (DSRC) is a short-range wireless protocol dedicated for automotive applications. Once a vehicle is plugged-in, the corresponding aggregator (e.g., parking deck operator) receives the battery state information (e.g., state-of-charge, state-of-health, voltage, and current) as well as customer information (e.g., customer identification, customer preference, and billing information). Multiple aggregators serve as middleware between the central controller (e.g., distribution company, and microgrid operator) and individual vehicles. Given the real-time information from multiple aggregators, the central controller performs the energy scheduling and sends back control signals periodically. This paper is to achieve the optimal power dispatch for a distribution system and reduce the financial risk of energy transactions from a distribution system operator's perspective.

2.1. Objective function

The objective function F is responsible for the most cost-effective operation of distribution systems. In this paper, the production cost of wind and solar energy is assumed to be negligible.

$$\min \quad F=\sum_{t}\sum_{j}c_j(P_j(t))+\sum_{t}\sum_{k}c_k(P_k(t))+\sum_{t}c_{grid}(P_{grid}(t)) +\sum_{t}\sum_{j}c_j^U(t), \tag{1}$$

where c_j, c_k and c_{grid} are the power production cost functions for the jth distributed generator, the kth distributed energy storage, and main utility grid, respectively; P_j, P_k and P_{grid} are the power output (kW) for the jth distributed generator, the kth distributed energy storage, and main utility grid, respectively; c^U is the start-up/shut-down cost for distributed generator.

To prolong the distributed energy storage device (DESD) life, the additional cost by frequent charging and discharging has to be taken into consideration. The battery degradation cost can be expressed as a function of the actual battery cycle life [17]. The depth of discharging (DoD) of the kth DESD (e.g., battery bank) is defined as:

$$DoD_k=\frac{E_{MG,k}}{\eta_{inv}E_k} \tag{2}$$

where $E_{MG,k}$ is the energy delivered or absorbed by the kth battery bank (DC, kWh); E_k is the rated energy capacity of the kth battery bank (DC, kWh); all the battery chargers are assumed to be identical with the same charging/discharging efficiency η_{inv}.

The relationship between battery cycle life (L) can be formulated as a function of DoD depending on the type of battery [17]. The relationship between battery cycle life (L) can be formulated as a function of DoD depending on the type of battery.

$$L=f(DoD) \tag{3}$$

$$L=\alpha\cdot DoD+\beta \tag{4}$$

where α, β are the battery cycle life coefficients.

Then the actual battery life $L_{E\text{-}DoD}$ (DC, kWh) is expressed as:

$$L_{E-DoD}=E\cdot L \tag{5}$$

where E is the rated energy capacity of battery bank (DC, kWh).

The unit battery degradation cost $C_{Degradation}$ (\$/kWh) is determined by the battery capital cost $C_{Battery}$ and the actual battery life $L_{E\text{-}DoD}$.

$$C_{Degradation}=\frac{C_{Battery}}{L_{E-DoD}}. \tag{6}$$

Therefore, the battery degradation cost (\$) for the kth battery bank is formulated as:

$$c_k=E_{MG,k}\cdot C_{Degradation,k}. \tag{7}$$

For distributed generators, the cost function can be formulated as:

$$c_j(P_j(t))=a_j+b_j\cdot P_j(t)+c_j\cdot P_j^2(t) \tag{8}$$

where a, b, and c are the production cost function coefficients.

For the main utility grid, the energy transaction payment can be formulated as:

$$c_{grid}(P,t)=P_{grid}(t)\cdot d(t) \tag{9}$$

where d is the grid electricity price (\$/kW).

2.2. System constraints

The system constraints considered in this paper are the same in the above three approaches. The system constraints include the following:

(1) Power balance

At any given time step, the left-hand term is the power generation from wind, solar, utility grid, DG and DES, respectively. The right-hand term includes the power loss, base load, and PEV