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Published in:
IEEE 18th International Conference on Environment and Electrical Engineering and 2nd Industrial and Commercial Power Systems Europe

Publication date:
2018

Document Version
Version created as part of publication process; publisher's layout; not normally made publicly available

Link to publication from Aalborg University

Citation for published version (APA):

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Stochastic Predictive Control of Multi-Microgrid Systems

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Abstract—This paper presents a stochastic predictive control algorithm for a number of microgrids connected to the same distribution system. Each microgrid includes a variety of distributed resources such as wind turbine, photo voltaic units, energy storage devices and loads. Considering the uncertainty of loads and renewable-based distributed resources, the power management problem is formulated in the framework of stochastic control. The microgrids operation are coupled through a joint probabilistic constraint which requires the power flow from utility to each microgrid limits below a certain value. Utilizing probabilistic distribution function of uncertain variables, the deterministic counterpart of the problem is derived and a close-optimal solution of the problem is achieved. The Monte-Carlo simulation analysis is used to justify the robustness characteristics of the solution.

Keywords—Multi-microgrid system; renewable energy resources; stochastic control; uncertainty management;

I. INTRODUCTION

Large penetration of distributed energy resources (DERs) into the power system has raised new challenges in recent years. Including a large number of small-scale power sources with their specific requirements and working conditions has resulted in more complex power management problems [1]-[2]. Accounting for these new requirements and challenges, microgrids have been introduced as a promising solution. Through aggregating DERs and local loads located in a neighborhood area under the control of an autonomous entity, a substantial reduction in the main grid’s organizational and computational burden can be achieved [3]-[5]. From the main grid’s point of view, a microgrid can be seen as a single entity with its net power imbalance parameter i.e., either a positive value showing surplus of energy or a negative one representing power shortage. In other words, microgrids play the role of a power source or an aggregated load in the big picture disregarding all the details and complexities.

However, the power production of renewable energy sources (RESS) including wind turbines (WT) and photovoltaic units (PV) which are the most common power resources of microgrids, are very difficult to forecast. Intermittent nature of power produced by RESs and variability of load patterns in a small-scale microgrid may increase its dependency on the upstream network and/or large-scale energy storage devices [6]. Considering recent developments in smart grids, cooperation among the neighboring microgrids may represent a promising control strategy in the next generation power systems [7].

Accordingly, a great effort has been made in recent years to operation management problem of networked-microgrids. In [8], a hierarchical optimization algorithm is presented to operation management problem of multi-microgrids. The information of each microgrid’s surplus, shortage and adjustable power is communicated to the central energy management system (EMS) in order to provide the local controllers with the optimal operating strategy. In [9], a model predictive control (MPC) approach is proposed to extract the optimal power scheduling of a cluster of interconnected microgrids. In [10], a three-phased algorithm based on cooperative MPC is proposed to minimize the total energy exchange of a multi-microgrid system with the utility as well as minimizing operational cost. In [11], a two-level hierarchical optimization scheme is designed in order to manage storage devices and power trading among macrogrid and interconnected microgrids in an optimal manner. Minimizing the load variance, transmission and generation cost and maximizing the consumers’ utility are included in the objective function. In [12], a multi-agent based hybrid optimization method is proposed for hierarchical energy management in multi-microgrid systems. In [13], energy management problem of a number of prosumers considering as small-scale microgrids is investigated. Results show cooperation among different prosumers will result in better performance in comparison with the stand-alone operational situation. In [14] and [15], coalitional game theory is utilized to partitioning the network of grid-connected microgrids to disjoint clusters. It is shown that through power sharing among microgrids the total system loss could be reduced. In [16], the same approach is adopted for the grid-independent microgrids. In [17], the internal and external power trading of multi-microgrids is modeled using a sequentially coordinated approach. Combined heat and power is also considered in the model in order to prevent unnecessary power trading with the mains. In [18], authors represent a comparison between different energy management systems including centralized, decentralized and hybrid systems and develop a nested EMS for interconnected microgrids. Proposed nesting approach is based on load priorities of each microgrid in the network.
One of the main challenges in operation management of microgrids is the intermittent nature of RESs and loads variability. Although a large number of algorithms have been developed for generation and load forecasting, their results are never exact. Consequently, the microgrid’s energy shortage or surplus may deviate from its estimated quantities and result in power flows deviation from scheduled values. Considering growing penetration of RES-based microgrids, large amount of power flow deviations may appear as grid disturbances and make the energy management problem of the macrogrid more challenging than before.

In this paper, in order to address these sources of uncertainty, the operation management problem of multi-microgrids is formulated in the framework of cooperative stochastic predictive control. Microgrids in a neighborhood area are coupled through a joint chance constraint which guarantees that the power flow from the main grid to all the microgrids in the local area will not violate the scheduled values with a specified confidence level. In other words, microgrids cooperate with each other to handle the uncertainties internally and not passing it to the upstream network. Utilizing probabilistic distribution knowledge of uncertain parameters, the deterministic counterpart of the problem is derived and a close-optimal solution of the problem is achieved. To justify the robustness characteristics of the solution, Monte-Carlo simulation analysis is also used. To the best of our knowledge, this approach has not been utilized in operation management problem of multi-microgrid systems.

In the following sections, first the problem formulation together with the chance-constraint predictive control is presented. The applicability and effectiveness of the proposed approach is then shown over a number of simulation studies. Finally, conclusion remarks are presented.

II. PROBLEM FORMULATION

The multi-microgrid system as shown in Fig.1, consists of $M$ heterogeneous microgrids connected to the same distribution system. It is assumed that in each microgrid, the production is based on RESs including WTs and PVs with different capacity and generation profiles. Moreover, each microgrid is equipped with a battery-based energy storage system. The state of charge (SOC) of the battery in each microgrid can be considered as a state variable which its evolution over time can be formulated as (1)-(3). Where, $a_i$ is the self-discharging factor of the battery and $P_{batt,i}(k)$ denotes the amount of charging/ discharging power of the battery at time step $k$ which is considered to be positive/negative during charging/discharging periods. Moreover, $C_{nom,i}$ is the battery nominal capacity and $P_{batt,i}$ is the amount of power which is transmitted from the utility to the $i^{th}$ microgrid. In (2), $d(k)$ shows the power imbalance of the microgrid which is considered the source of uncertainty in this paper. In (3), $\bar{p}_{wt,i}$, $\bar{p}_{pv,i}$ and $\bar{l}_i$ show the predicted amounts of WT and PV production and the value of forecasted aggregated load, respectively.

\[ SOC_i(k+1) = a_iSOC_i(k) + \frac{1}{C_{nom,i}} P_{batt,i}(k) \]  \hspace{1cm} (1)

\[ d_i(k) = \bar{p}_{wt,i}(k) + \bar{p}_{pv,i}(k) - \bar{l}_i(k) \]  \hspace{1cm} (2)

\[ P_{batt,i}(k) = P_{c,i}(k) + d_i(k) \]  \hspace{1cm} (3)

It is assumed that the power extracted from the utility by each microgrid in the system should be within a pre-specified limit. In other words, energy exchange with the utility and each of microgrids is only acceptable if constraint (4) is satisfied [9].

\[ P_{\text{min}},i \leq P_{c,i}(k) \leq P_{\text{max}},i \quad i = 1,2,...,M \]  \hspace{1cm} (4)

However, considering intermittent nature of RESs production and variability of loads, $d_i(k)$ is an uncertain variable. Accordingly, $P_{c,i}$ will be also an uncertain variable meaning that satisfying a constraint in the form of (4) cannot be fully guaranteed for each microgrid. In this paper, it is proposed that in a cooperative network of microgrids, in order to manage uncertainties internally within the local network, microgrids in a local area cooperate with each other to keep the power flow from utility to each microgrid within scheduled interval. Applying stochastic predictive control, constraint (4) can be reformulated as a joint chance constraint in the form of (5) [19]. Where, $P$ is the probability operator and $1-\rho$ denotes a pre-specified confidence level.

\[ P\left(P_{\text{min}},i \leq P_{c,i}(k) \leq P_{\text{max}},i \right) \geq 1 - \rho \]  \hspace{1cm} (5)

This constraint could be considered as a joint constraint through making all the microgrids in the local area to satisfy it simultaneously. Considering constraint (5), it is guaranteed that the probability of satisfying constraint (4) for each microgrid at the same time, will be higher than $1-\rho$. However, solving an optimization problem with a joint chance constraint in the form of (5) is a challenging task as requires the evaluation of an integral of multi-variable probability distribution function. Utilizing the decomposition approach introduced in [19] the problem can be approximated with replacing the stochastic constraint with $M$ individual chance constraints and a new coupling constraint represented through (6)-(7). Where, $\delta_i$ is interpreted as the risk bound of each microgrids determining through a risk allocation process [19].

Adopting cooperating strategy, the EMS is responsible for allocating risk parameters to each individual microgrid. According to (7), the sum of risk parameters is upper bounded by the total amount of risk $\rho$ through minimizing the total cost of the multi-microgrid system. Solving an optimization problem with individual chance-constrains is more straight forward as only the evaluation of single-dimensional probability distribution functions are required.

\[ P\left(P_{\text{min}},i \leq P_{c,i}(k) \leq P_{\text{max}},i \right) \geq 1 - \delta_i(k) \quad i = 1,2,...,M \]  \hspace{1cm} (6)

\[ \sum_{i=1}^{M} \delta_i(k) \leq \rho \]  \hspace{1cm} (7)

However, through suitable tightening of feasible region, the probabilistic constraints could be reformulated as deterministic constraints using the statistical characteristics of uncertain variable. Assume that $d_i(k)$ follows a normal distribution and forecasted values of power imbalance are considered as its expected values $\bar{d}_i(k)$.
The deterministic counterpart of the energy management problem at each time instant $t$ can be represented as (8)-(16). Where, $N$ is the optimization horizon. In (8), $C_i'(k)$ denotes the price of transferring one kilowatt hour energy from utility to $i$th microgrid in time interval $k$. In (13)-(14), $f(1-\delta_i)$ is the inverse of cumulative distribution function of a standard normal variable with zero mean and unity variance as shown in (16). Moreover, $U_g(k)$ represents the variance value of variable $P_{g,i}$ which can be calculated through exploiting statistical characteristics of $d_i(k)$. According to the presented formulation, solving a convex optimization problem with linear and nonlinear constraints is required during adopted control horizon.

$$\min \left\{ \sum_{i=1}^{M} \sum_{k=1}^{N} C_i'(k) P_{g,i}(k) \right\}$$

$$SOC_i(k+1) = SOC_i(k) + P_{batt,i}(k)$$

$$P_{batt,i}(k) = P_{g,i}(k) + \bar{d}_i(k)$$

$$P_{\text{min}}^{\text{batt},i} \leq P_{\text{batt},i}(k) \leq P_{\text{max}}^{\text{batt},i}$$

$$SOC_i^{\text{min}} \leq SOC_i(k) \leq SOC_i^{\text{max}}$$

$$P_{g,i}(k) \leq P_{g,i}^{\text{max}}(k) - \sqrt{U_g(k)} f(1-\delta_i(k)) \quad i = 1,2,\ldots,M$$

$$P_{g,i}(k) \geq P_{g,i}^{\text{min}}(k) + \sqrt{U_g(k)} f(1-\delta_i(k)) \quad i = 1,2,\ldots,M$$

$$\sum_{i=1}^{M} \delta_i(k) \leq \rho$$

$$f(\lambda) = \sqrt{2} \erf^{-1}(2\lambda - 1)$$

III. SIMULATION RESULTS

In this section, in order to clarify the effectiveness of the proposed algorithm, an exemplary multi-microgrid system with two heterogeneous RES-based microgrid will be considered. It is assumed that the maximum available power from RESs should be exploited. The total capacity of storage devices in microgrid 1 and 2 is assumed to be equal to 30 kWh and 38 kWh, respectively. The values of $SOC_{\text{min}}^{\text{soc}}$ and $SOC_{\text{max}}^{\text{soc}}$ in each microgrid are set to 20% and 80% of the battery nominal capacity. The risk factor $\rho$ is assumed to be equal to 0.4. In order to modeling the microgrids’ power shortage/surplus, (17) and (18) have been used. Adopting proposed methodology, each microgrid transmits information of its surplus/shortage of power during the optimization horizon which is set to 24 hours to the EMS.

In EMS, considering coupling constraint among microgrids and temporal relation of consecutive decisions, the non-linear convex optimization problem introduced through (8)-(16) is solved. Normalized values for state of charge of batteries for two scenarios including a deterministic scenario without considering uncertainty of generation and demand as well as a stochastic scenario are shown in Fig. 2. As it can be seen in Fig. 2, in stochastic scenario, considering generation and demand uncertainty, it is preferred to keep the energy level of storage devices in higher quantities to avoid any risk of power mismatch and fluctuation at the supply and demand sides. Table. I represents expected amount of power to be requested from the utility in each scenarios. Adopting proposed strategy, in stochastic scenario EMS is arrived at a conservative strategy through suitably tightening of its feasible region and relying more on energy storage devices. For comparison purpose, total operation cost in terms of monetary unit (M. U) is also represented in Table. I.

$$2\text{sign}(\sin(\frac{\pi}{12}(k+6)))) - 1$$

$$2\text{sign}(\sin(\frac{\pi}{12}(k+12)))) - 1$$

In order to justify the robustness characteristics of the solution, Monte-Carlo simulation analysis is used to generate random scenarios to represent the intermittent nature of WT and PV as well as load fluctuations. Fig.3 represents the error bars under two scenarios for the probabilistic joint chance constraint satisfaction. As it was expected, under stochastic scenario the probability of satisfying the joint constraint is higher than 1-$\rho$ in all the hours which confirms the superiority of stochastic approach. However, it is worth mentioning that this robustness has been achieved at higher operation cost.
In this paper, cooperative operation management problem of a RES-based multi-microgrids system was formulated in the framework of chance constrained predictive control. Considering intermittent nature of RESs' production and variability of loads, microgrids cooperated with each other through a joint probabilistic constraint. To justify the robustness characteristics of the solution, Monte-Carlo simulation analysis was also used. Results showed that through adopting stochastic approaches and cooperative operation management strategies as well as appropriate utilization of energy storage devices, microgrids performance can be improved. Moreover, the main grid disturbances resulted from power deviation of grid connected microgrids can be considerably decreased.

### REFERENCES


