Model Predictive Control-based Optimal Coordination of Distributed Energy

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Abstract
Distributed energy resources, such as renewable energy resources (wind, solar), energy storage and demand response, can be used to complement conventional generators. The uncertainty and variability due to high penetration of wind makes reliable system operations and controls challenging, especially in isolated systems. In this paper, an optimal control strategy is proposed to coordinate energy storage and diesel generators to maximize wind penetration while maintaining system economics and normal operation performance. The goals of the optimization problem are to minimize fuel costs and maximize the utilization of wind while considering equipment life of generators and energy storage. Model predictive control (MPC) is used to solve a look-ahead dispatch optimization problem and the performance is compared to an open loop look-ahead dispatch problem. Simulation studies are performed to demonstrate the efficacy of the closed loop MPC in compensating for uncertainties and variability caused in the system.

1. Introduction
Integrating distributed energy resources (DERs), such as renewable resources and energy storage, can allow for economical and environmentally friendly system operation. However, wind and solar resources will have adverse effects due to: variability and low capacity factors making the net demand profile steeper, relatively larger forecast errors for longer horizons, and operational performance issues. New control strategies ensuring proper coordination between the DERs and other conventional sources can overcome these issues and improve system reliability.

Several coordination strategies of DERs, to provide ancillary services (i.e., scheduling, dispatch, balancing, contingency response, etc.) have been explored in [1]-[6]. A power management strategy for wind-diesel-battery energy storage systems (BESS) is presented in [7]. Diesel and energy storage power setpoints are dispatched, using day-ahead wind and load forecasts. The goal was to minimize diesel generator operating costs, as well as, costs related to battery lifetime.

In [8], a combination of centralized and decentralized coordination strategies for a rural microgrid, containing wind and diesel generators, BESS, and demand response was studied. The objectives for the coordination strategies were to maintain system frequency close to nominal and to reduce fossil fuel generator movement by allowing energy storage devices to compensate wind variability. Arbitrary control inputs were selected only to show the effectiveness of the control coordination strategies. The authors of [8] recognized the need for an optimally coordinated control scheme between different DERs.

To address the issues of variability and uncertainty, in [9]-[12], a model predictive control (MPC) approach is introduced. The strategy is based on dispatching power at minimal cost, assuming that energy storage is not available, that renewable sources are dispatchable, and that only short-term wind forecasts are reliable. In [13], a control strategy is proposed, in which energy storage follows wind and net load variability based on using a threshold as the control input. Specifically, the storage unit charges if wind generation is greater than the threshold and discharges if wind is less than the threshold value. It was also shown that the control strategy for compensating net load variability had a better performance as compared to compensating only wind variability.

One of the contributions of this work over the conventional approach of dispatching storage power directly is to show how the net-load-variability-based
control strategy allows the balancing diesel generator to make smoother transitions. As a result, the battery storage balances power along with the isochronous generator when there are mismatches in forecasts of load demand and wind power.

Another way in which this work differs from the work presented in [9]-[13] is that it includes maximization of wind utilization explicitly as part of the dispatch problem. In this respect, it directly addresses the problem of variability and uncertainty associated with maximizing wind utilization. Model predictive control is used to optimally coordinate energy storage and diesel generators to maximize wind penetration while maintaining system economics and normal operation performance. The goals of the optimization problem are to minimize fuel costs and maximize the utilization of wind while considering equipment life of generators and energy storage. Simulation studies are used to evaluate the performance of the different control strategies and to demonstrate the effectiveness of the closed loop MPC in compensating for uncertainties and variability caused in the system.

This paper is organized as follows. In Section 2, a brief description of the system is given. An optimal control coordination scheme based on using MPC, to solve the look-ahead dispatch problem, is presented in Section 3. In Section 4, case studies are presented that demonstrate the effectiveness of the optimal control coordination strategy. Finally, conclusions are given in Section 5.

2. System Description

The isolated power system under consideration consists of diesel generators, a battery energy storage system, a wind power plant, and residential loads. The DERs are coordinated to maximize wind power use and reduce diesel generator movement; the storage compensates for net load variability and one generator provides real-time power mismatch. Based on the application or time scale of interest (minutes to hours), static models can be used to represent the system. In this work, dynamics are introduced by set point changes in power generation levels and in storage threshold in response to changes in loads and wind generation. For this investigation, system losses are neglected. In this section, a description of the system is given in terms of the relationships among load, conventional generation, storage, wind generation, and wind curtailment. The system dynamics of the isolated power system at time step \( k \) can be expressed by the following difference and algebraic equations:

\[
P_G(i+1) = P_G(i) + \Delta P_G(i) , \ i = 2,...,G \\
T(k+1) = T(k) + \Delta T(k) \\
SOC(k+1) = SOC(k) - \alpha P_e(k) \\
P_{intra}(k) = P_L(k) - P_L(k) - P_e(k) - \sum_{i=2}^G P_G(i) \quad (4)
\]

where \( P_G(k) \) is the output power of the \( i \)-th diesel generator, \( \Delta P_G(k) \) is the power setpoint change of the \( i \)-th diesel generator, \( T(k) \) represents the threshold setpoint for BESS, \( SOC(k) \) is the state of charge of the BESS, \( \alpha \) is a constant given by 
\[
\alpha = \frac{\eta}{E_{max}} \quad \text{where,} \quad \Delta t \quad \text{is the time step duration (hr.),} \\
\]

\( E_{max} \) is the energy capacity of BESS (kWh), \( \eta \) is the efficiency of the BESS, \( P_L(k) \) is the lumped load power, \( P_e(k) \) is the total power generated by the wind power plant, and \( P_{intra}(k) \) represents the wind power absorbed by the BESS. The physical constraints on diesel generator power outputs, diesel generator ramp rates, and BESS energy capacity are

\[
P_{min}^G \leq P_G(k) \leq P_{max}^G \\
|\Delta P_G(k)| \leq R_{max}^G \\
SOC_{min} \leq SOC(k) \leq 1
\]

where \( P_{min}^G \) and \( P_{max}^G \) are the minimum and maximum output power of the \( i \)-th diesel generator, and \( R_{max}^G \) is the maximum allowed power change of the \( i \)-th diesel generator from one time step to the next. In the above, \( SOC_{min} \) is chosen high enough to avoid low State of Charge (SOC). Operating a BESS at low SOC (e.g. \( SOC(k) \leq 0.3 \)) drastically degrades battery life which needs to be avoided.

To allow diesel generators and the BESS to both compensate for the variability and uncertainty associated with high penetration, the DER coordination strategy that uses the BESS to compensate variability in net load (total load – wind power), is given in (8) and (9).

\[
P_L(k) = P_L(k) - P_e(k) - T(k) \quad (8)
\]

\[
P^w_e(k) = \min \left \{ P_L(k), P_L(k) - T(k) - \frac{SOC(k) - 1}{\alpha} \right \} \quad (9)
\]

If net load is greater than the threshold value, the BESS will charge; if less than the threshold, it will discharge. The benefit of the DER coordination strategy (e.g. benefit of the threshold \( T(k) \) over
dispatching the storage power $P^s_k$ (directly) is shown in Figure 1 and Figure 2. Figure 1 shows the isochronous (balancing) generator for a case where the storage power is directly dispatch (DER coordination strategy is ignored) and where storage threshold is dispatched, respectively. Results show that considering the DER coordination strategy encourages the isochronous generator to make smoother transitions over time as expected. Figure 2 shows the state of charge of the storage when the coordination strategy is ignored and considered, respectively. It can be seen that the performance of the SOC is comparable in both cases i.e. when the power is directly dispatched and when using the threshold based coordination strategy.

During normal conditions, the power balance of this isolated power system is achieved by the isochronous generator. This generator operates under integrator control to maintain system frequency by maintaining the power balance. It should be mentioned that only one generator has isochronous control to avoid power oscillations among resources [14]. These power oscillations appear in practice because of measurement errors and uncertainty in parameters. When there is excessive wind generation, the isochronous generator will not be able to maintain the power balance if wind power is not curtailed. The strategy for curtailing wind power is based on the dump load strategy presented in [15]. The wind curtailment logic is as follows,

$$
\begin{align*}
P_{Gi} &= P_{Gimin} \quad \text{and} \quad P_{curtail} = P_{Gimin} - P_{imbalance} \\
\text{else} & \\
P_{Gi} &= P_{imbalance} \quad \text{and} \quad P_{curtail} = 0
\end{align*}
$$

where $P_{curtail}$ is the amount of wind to be curtailed which can be re-written, more compactly, as

$$
P_{curtail} = \max \left\{ 0, P_{Gimin} - \sum_{i=2}^{G} P_{Gi}(k) + P_{Gi}(k) + P_{k}(k) - P_{L}(k) \right\}
$$

The constraint on the amount of wind to be curtailed is given by

$$
0 \leq P_{curtail}(k) \leq P_{max_{curtail}}
$$

where $P_{max_{curtail}}$ is the maximum amount of wind curtailed in the system.

### 3. Model Predictive Control-based optimal coordination strategy

Even though day-ahead forecasts for load demand are reliable, day-ahead forecasts for wind are not. The conventional dispatch problem is implemented in an open loop control manner, which means that the optimization problem is solved over an entire horizon once and the resulting sequence of control inputs are implemented at the corresponding time steps.

An alternative technique to solve the multi-objective optimal control problem is to use MPC, where at every step a finite horizon optimal control problem is solved using feedback from the system. The control action at each step is computed on-line rather than using a pre-computed, off-line, control law. In this manner, MPC is considered closed loop and has the ability to compensate for additional uncertainty and variability caused by high penetration of renewable energy resources.
3.1. Description of Model Predictive Control

Consider the following system dynamics given by,

\[ x(k+1) = f(x(k), u(k), d(k)) \]  \hspace{1cm} (13)

MPC uses, at each sampling instant, the system’s current state, input and output measurements, and the system’s model to calculate, over a finite horizon, a future control sequence. This control sequence optimizes a given performance index and satisfies constraints on the control action. Let \( \hat{x}_k^i = \hat{x}(k+i|k) \), \( u_k^i = u(k+i|k) \) and \( \hat{d}_k^i = \hat{d}(k+i|k) \) denote the predicted state, derived control and predicted disturbance based on the current measurement, \( x(k) \). The control objective is to find a sequence of control inputs over a given prediction horizon, \( N \), such that a given cost function and constraints are satisfied. The above control sequence will result in a predicted sequence of state vectors that can then be used to compute the predicted sequence of system outputs. Using this information, the control can be applied to the system and the process is repeated with the state measurement of the next time step serving as an initial condition to compute the control input. The MPC can be described mathematically as follows

minimize

\[ J = \sum_{i=1}^{N-1} J_i(\hat{x}_k^i, u_k^i) \]  \hspace{1cm} (14)

subject to:

\[
\begin{align*}
\hat{x}_{k+1}^i &= f(\hat{x}_k^i, u_k^i, \hat{d}_k^i) \\
l(\hat{x}_k^i, u_k^i, \hat{d}_k^i) &= 0 \\
h(\hat{x}_k^i, u_k^i, \hat{d}_k^i) &\leq 0,
\end{align*}
\]  \hspace{1cm} (15)

where the functions \( l \) and \( h \) represent the equality and inequality constraints respectively.

3.2. MPC-based optimal dispatch

When considering optimal coordination of DERs in the presence of high renewable penetration, economics is not the only concern. It is difficult to translate all goals into cost terms ($\$ \). Therefore, the problem should be formulated as a multi-objective optimization problem. The goals are to: 1) minimize fuel costs of diesel generators, 2) minimize changes in power output of diesel generators reducing mechanical wear and tear, 3) minimize costs associated with low battery life of energy storage, 4) maximize the ability of isochronous generators to provide real-time balancing, and 5) maximize wind power utilization. The optimal dispatch problem is therefore formulated as a multi-objective optimization problem. There are many ways to handle multi-objective optimization problems. The weighted sum method is a classical and widely-used method that combines the set of objectives into a single-objective optimization problem by multiplying individual objectives by user defined weights [16]. Generally, if the objective function is convex and all weights are positive, minimizing the objective function has sufficient conditions for Pareto optimality, but not the necessary conditions [16]. The weights in this work are chosen arbitrarily by assuming the relative importance is known. Other multi-objective optimization techniques could be explored that do not require \( a \ priori \) information about the preferences of the decision maker and that can guarantee Pareto optimality. However, this is beyond the scope of this work.

In this work, MPC is used to solve the multi-objective optimization problem and the cost function is defined as

\[
J = \sum_{t=1}^{K} \left[ w_1 \sum_{j=1}^{G} C(t) \hat{P}_{\text{loss}}(k+i|k) + w_2 \left( \hat{P}_{\text{curtail}}(k+i|k) \right)^2 \right] \]  \hspace{1cm} (16)

where \( w_1 \) is the penalty associated with fuel costs of diesel generators and \( w_2 \) is the penalty associated with wind curtailment. The states chosen to represent the prediction model of the system plant defined in (1)-(4).

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where \( w_1 \) is the penalty associated with fuel costs of diesel generators and \( w_2 \) is the penalty associated with wind curtailment. The states chosen to represent the prediction model of the system plant defined in (1)-(4).
After obtaining the control inputs $\Delta P_{G_j}(k)$, $j = 1, \ldots, G$ from MPC, the control input $\Delta T(k)$ can be determined by solving

$$
\Delta T(k) = \sum_{j=1}^{G} \Delta P_{G_j}(k) - \Delta P_{\text{wind}}(k) + \left( \hat{P}_L(k) - \hat{P}_L(k+1) \right) - \left( \hat{P}_L(k+1) - \hat{P}_L(k) \right) 
$$

(19)

Then $\Delta P_{G_j}(k)$, $j = 1, \ldots, G$ and $\Delta T(k)$ can be applied to the plant. With the cost function and prediction model defined in (14) and (15), the MPC-based optimal dispatch problem can be re-formulated as follows

$$
j(\hat{x}_k) = \sum_{i=1}^{N-1} \left[ \hat{x}_{i+1}^T \hat{Q} \hat{x}_i + c^T \hat{x}_i \right] 
$$

(20)

subject to:

$$
\begin{bmatrix}
\hat{P}_{G_1}(k+1|k) \\
\vdots \\
\hat{P}_{G_G}(k+1|k) \\
\hat{SOC}(k+1|k) \\
\hat{P}_{\text{curtail}}(k+1|k)
\end{bmatrix} =
\begin{bmatrix}
0 & 0 & \cdots & 0 & 0 \\
0 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & 0 \\
0 & 0 & \cdots & 0 & w_2
\end{bmatrix}
\begin{bmatrix}
\hat{P}_L(k+1|k) \\
\vdots \\
\hat{P}_L(k+1|k)
\end{bmatrix} +
\begin{bmatrix}
\alpha_1 G_{1,1} & 0 & 0 & 0 \\
0 & \alpha_1 G_{2,1} & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
I_G & 0_{G,1} & 0 \\
0_{1,G} & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
\hat{P}_L(k+1|k) \\
\vdots \\
\hat{P}_L(k+1|k)
\end{bmatrix}
$$

where,

$$
\hat{x}_i = \begin{bmatrix}
\hat{P}_{G_1}(k+1|k) \\
\vdots \\
\hat{P}_{G_G}(k+1|k) \\
\hat{SOC}(k+1|k) \\
\hat{P}_{\text{curtail}}(k+1|k)
\end{bmatrix}
$$

(21)

subject to:

$$
\hat{x}_\text{min} \leq \hat{x}_i \leq \hat{x}_\text{max}
$$

4. Simulation studies

The open loop implementation of the dispatch problem and the proposed MPC-based closed loop strategies were both applied to the test system under different number of wind units and different days.

4.1. Description of test cases

The test system consists of two diesel generators rated at 2500kW, a 3600kWh-rated BESS, a wind power plant (data obtained from [18]), wind energy curtailment (modeled as dump load) and an aggregate load of 1500 houses ([17]). System losses are neglected. One generator is in charge of real-time system balance, compensating for wind and load uncertainty not covered by the dispatch algorithms. The other generator operates at the given set points defined by the dispatch algorithm. The BESS compensates for net load variability given a threshold set point.

Wind disturbance is modeled as an autoregressive integrated moving average (ARIMA) model

$$
\left(1 - \sum_{i=1}^{p} \phi_i L^{-i}\right)\left(1 - L^{-d}\right)^d P_v(k) = \left(1 - \sum_{i=1}^{q} \theta_i L^{-i}\right) \epsilon(k)
$$

where $p$, $d$, and $q$ are the identified orders of the autoregressive (AR), integrated (I), and moving average (MA) parts, respectively, $L$ is a lag operator, $\phi_i$ are the parameters of the AR part, $\theta_i$ are the parameters of the MA part, and $\epsilon(k)$ is the error term. These univariate time series models allow forecasted values to be calculated as a linear function of previous values. The Box-Jenkins approach [19] was used to select the parameters and orders of the models and to evaluate model adequacy. In the studies, load is assumed to be perfectly forecasted.

An example of the actual load and wind profiles for 1 and 2 wind units on day 1 is shown in Figure 3. Ideal forecasts are assumed for the load since day ahead forecasts for loads can be predicted within 1-5%, as shown in [20]. The actual versus predicted wind for a 24-hr prediction horizon is shown in Figure 4. This predicted wind profile is used in the open-loop day-ahead dispatch problem. The actual versus predicted wind for a 1-hr prediction horizon at every control step, using the ARIMA model, is shown in Figure 5. The predicted wind is used in the MPC based dispatch problem which motivates the need for the closed-loop control strategy.
4.2. Comparison of MPC and open loop optimal dispatch strategies

In the following studies, a medium wind penetration case of 4 wind units is considered. The responses of the different DERs for the open loop dispatch cases are shown in Figure 6. Generator 2 follows the set points given as expected. The BESS follows the actual net load variability until the SOC reaches its lower limit at which point generator 1 supplies the additional power needed. In general, there is wind curtailment when there is excessive wind generation or when generator 1 has to go below its minimum value to supply the load. The wind curtailment is sometimes negative because the isochronous generator (generator 1) would have to go beyond its maximum capacity limit to supply the load. This implies that the total generation is insufficient to supply the load, in this case, which causes the need to shed load. The case of considering load control was not within the scope of this paper, although it is a topic of ongoing research pursued by the authors.

The responses of the different DERs, for the MPC-based closed loop control strategy are shown in Figure 7. Generator 1 balances power and Generator 2, once again follows its optimal setpoint. The BESS compensates for net load variability and the SOC stays above its minimum value of 0.3, which in turn implies that the life-cycle of the energy storage unit is being improved. The amount of wind curtailed in the closed-loop case is less than the open-loop case and also it does not take negative values since the DERs are better coordinated. This is because better setpoints are given to the resources based on continuous updates and better predictions.

A comparison of the individual objective costs and the total cost for a prediction horizon of 6 steps is given in Figure 8. The total cost for the open loop case (9.81) is higher than the closed loop case (7.60) which implies that the MPC-based closed loop strategy ensures a lower fuel cost and lower wind curtailment (or higher wind utilization).
4.3. Comparison of wind utilization using MPC and open loop

The performance of the open and closed loop control strategies is compared for different number of wind units and for different daily wind profiles. The total cost and utilization for the open and closed loop control strategies over different number of wind units is shown in Figure 9. The average utilization over the time period for the open loop case is 66.82%, and for the closed loop is 72.6%. The average cost for the open loop case is 8.90 and for the closed loop case is 7.63. This implies that the MPC-based closed loop strategy has a significantly lower cost while maintaining a comparable level of wind utilization as the number of wind units is increased.

The total cost and utilization for the open and closed loop control strategies over different days is shown in Figure 10. The average utilization over the time period for the open loop case is 64.86% and for the closed loop is 70.93%. The average cost for the open loop case is 10.38 and for the closed loop case is 7.46. This indicates that the MPC-based closed loop strategy has a significantly lower cost while maintaining a comparable level of wind utilization over the course of the month.
5. Conclusions

An optimal MPC-based control strategy is proposed for coordinating different DERs for an isolated power system. The simulation studies indicate that the performance (meeting individual objectives and total cost) of the proposed MPC-based closed loop strategy is better than the open loop implementation of the dispatch problem. It is also shown that the closed loop MPC strategy has a much better overall performance (lower cost and higher wind utilization) under varying wind penetration levels and over different wind profiles for different days. Although the results presented in this work are for a simple model consisting of a few diesel generators, storage and wind units the MPC based optimal coordination strategy can be applied to more complex systems. A subject of ongoing research is to apply the technique proposed in this paper to the test platform for the rural microgrid developed in [8] which is based on the IEEE 34 bus test feeder system. Furthermore, both isolated and grid connected modes of operation will be considered.

6. References


