Real-Time Optimization of Distribution System Considering Interaction Between Markets

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Abstract—In this paper a novel architecture for real-time optimization is proposed based on Receding Horizon Control (RHC). The proposed architecture is capable of including real-time system data and can incorporate uncertainties in resources and market price. The main focus is to interface an active distribution network to wholesale market and neighboring Distribution System Companies (DISCOs) incorporating real-time price prediction. The effectiveness of proposed method is examined on a modified 32-bus distribution network incorporating Distributed Generators (DGs) such as wind and storage, neighboring DISCOs and wholesale market entities. It has been observed that the proposed method outperforms conventional methods and has the potential to implement dynamic stochastic optimal power distribution in modern power grid.

Index Terms—Receding Horizon Control, Real-time Optimization, Wholesale Markets, Distribution System.

I. INTRODUCTION

During the past decade power distribution network has seen several changes such as evolution of new energy resources, distributed storage, and high power electrical devices such as electric vehicles. There has been considerable changes in the network components such as smart measurements, digitized equipments and communication systems. Various smart grid functions has changed the nature of distribution network from passive to an active network as well. Increasing number of storages, distributed generation, better ramping of generators and tendency of small distribution network to participate in price market added more degree of freedom to optimization problem in DISCOs. Also, stochastic variables such as pricing, and uncertain energy generation has added new aspect to dynamic Optimal Power Flow (OPF) problem. This new topology of power distribution network has intensified the need for real-time optimization methods that can handle real-time data and stochastic nature of price and energy sources [1]-[3].

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The conventional OPF techniques use nonlinear programming (NLP) based methods. These approaches are natively complex and have real convergence issues. Most common methods are Quadratic programming (QP), Newton-based techniques, linear programming (LP), Interior Point methods and Genetic Algorithms based techniques. Approximations, accuracy and formulation relaxations are the three major issues in such conventional techniques. Recently heuristic algorithms and evolutionary techniques have been attempted as OPF methods [4], [5]. Of the most promising techniques are the Model Predictive Control (MPC) approaches [6]-[8]. This method has the capability to promote constrained based optimization which is extremely critical in modern power grid optimization as the this can incorporate real-time data exchange and manage uncertainties.

The need for distribution system optimization with market transactions including distributed energy resources (DER) have been discussed in the literature earlier. Reference [9] indicates the main aspects of DER, and the challenges and potential solutions for implementing Demand Response in smart grid market. Reference [10] proposes a new algorithm for distribution management system (DMS) that can be applied to active distribution networks and [11] proposes a new algorithm for distribution system operation. However, these approaches did not include the stochastic variability of the DERs. Several forecasting methods have been proposed that integrates variability and changes in the resources. Reference [12] introduced a method for maximizing the profits for market participants. Reference [13] and [14] discusses a study with mixed integer non-linear programming (MINLP) approach for determining optimal location and number of distributed generators in hybrid electricity market. Reference [15] discusses an overall review of the wind power forecasting methods.

It is apparent that the important aspects of integrating DER’s into the conventional power distribution system is energy management and control. For this system dynamics and control model should be integrated to the analysis techniques such as OPF. So far, there has been no coherent method that integrates system models with dynamics and control with OPF. In this paper we propose a novel real-time optimization method using Receding Horizon Control (RHC) within ACOPF, incorporating stochastic market pricing and distributed energy resources with storage.

The paper is organized as follows. In section II part A, we discuss the proposed RHC method and how this can be included in an real-time optimization framework; As it will be discussed, the main advantage of the formulation is that this approach allows stochastic dynamic real-time optimization of the modern power grid. Figure 1 illustrates the overall algorithmic framework. Stochastic price model and proposed formulation of price prediction toward time horizon based on previous real price samples at every time step is also discussed in Section II part A. General ACOPF formulation is presented in section II B. Case studies and implementation of proposed method on a modified 32 power distribution bus system including wholesale market, neighboring Distribution Company (DISCO), Wind Farm and storage is presented in section III. Conclusions are in section IV.

II. PROPOSED METHOD

The overall proposed algorithm include real-time optimization based on prediction and market price transactions. Figure 1 illustrates the overall algorithmic framework. Two main interactive algorithms in the proposed method are RHC formulation and overall ACOPF formulation and integration. First RHC formulation including a methodology for price forecasting is discussed.

A. Proposed RHC methodology for price forecasting

The Receding Horizon Control (RHC) method can handle constrained OPF problem which needs the prediction regarding future inputs and parametric variations such as load and market price based on real-time feedback from the system. This method generates the control variables over a fixed horizon by minimizing the objective function every time step. The proposed RHC methodology can be described as follows:

- At time step \( t \), define the constrained objective function and solve over the time horizon \( [t : t + T - 1] \) to generate the control variables for every step in horizon. The prediction of future variable based on real-time current state and previous \( N \) samples is included in problem for optimization.
- Measure the system states at time \( t + 1 \) by applying the results from the first step of control action.
- Repeat the horizon control optimization at time \( t + 1 \) over the time interval \( [t + 1 : t + T] \).
The above mentioned process is repeated at every time step during the grid operation. The system scheduling would not be stopped at horizon and continues as long as the system is in operation. This method provides the degree of freedom for choosing the time step and also the total horizon. Handling time horizon brings in the ability to include historic data and predict the results in near future real-time. This optimization process also provides the capability to handle the dynamical systems such as energy storage.

One of the objective of the proposed method is to include price prediction. Generally the operation of DISCO is power exchange from wholesale market based on revenue. Thus, real-time operation of active power distribution network should include meticulous price prediction. In the proposed method, real-time price prediction is achievable based on the integration of price forecasting model within RHC. Stochastic models for wholesale market price are based on different random variables [16]. Three basic random variable used in models are normal distribution, log Normal Distribution, and Weibull distribution. In this formulation, the wholesale market price is considered as a stochastic variable and the price of neighboring DISCO is considered as a deterministic 24 steps variable. Out of various stochastic price models we assign a multi variable normal distribution as a wholesale price model for 24 hours.

The density function for this model is as follows:

\[
f(p_1, p_2, \ldots, p_{24}) = \left( \frac{1}{2\pi} \right)^{24} \left( \frac{1}{\det(COV_{i,j})} \right)^{\frac{1}{2}} \exp \left[ -\frac{1}{24} \sum_{i,j=1}^{24} (x_i - \mu_i) COV_{i,j} (x_j - \mu_j) \right]
\]  

(1)

From the density function the mean and covariance matrices for 24 hours are estimated. For analysis purpose sample data has been gathered from the Hourly Ontario Energy Price (HOEP). Then the last \( N \) step price data is used to modify the price prediction for the horizon time period by the derivation of conditional expectation expression. The method of linear regression in the joint distribution variables is deployed within the structure of RHC in order to improve the accuracy of wholesale market price prediction. At every time step, the price of next \( T \) hours is predicted based on real data gathered at the current instant and \( N-1 \) previous price samples. Conditional expectation of price \( P_t \) given current real-time and \( N - 1 \) previous data, is estimated as linear function of \( N \) sampled data. The proposed RHC price prediction formulation is presented in (2).

\[
\hat{P}_{k(t)} = E \{P_k|P_t, P_{t-1}, \ldots, P_{t-N+1}\} = \alpha + \beta P
\]  

(2)

where:

\[
\begin{bmatrix}
\alpha \\
\beta
\end{bmatrix} = f(P, E, COV)
\]

\[
\alpha = E \{P_k\} \cdot \beta
\]

\[
\beta =
\begin{bmatrix}
\frac{E((P_t - E(P_t)))(P_k - E(P_k))}{E(P_t - E(P_t))^2} \\
\frac{E((P_{t-1} - E(P_{t-1}))(P_k - E(P_k)))}{E(P_{t-1} - E(P_{t-1}))^2} \\
\vdots \\
\frac{E((P_{t-N+1} - E(P_{t-N+1}))(P_k - E(P_k)))}{E(P_{t-N+1} - E(P_{t-N+1}))^2}
\end{bmatrix}
\]

\[
COV = \begin{bmatrix}
COV_{1,1} & COV_{1,2} & \cdots & COV_{1,24} \\
COV_{2,1} & COV_{2,2} & \cdots & COV_{2,24} \\
\vdots & \vdots & \ddots & \vdots \\
COV_{24,1} & COV_{24,2} & \cdots & COV_{24,24}
\end{bmatrix}
\]

\[
P = \begin{bmatrix}
P_{t-1} \\
P_{t-2} \\
\vdots \\
P_{t-N+1}
\end{bmatrix}
\]

\[
E = \begin{bmatrix}
\mu_{t-1} \\
\mu_{t-2} \\
\vdots \\
\mu_{t-N+1}
\end{bmatrix}
\]

In (2), the coefficients \( \alpha \) and \( \beta \) are determined from the expectations \( E \{P_1\}, E \{P_2\}, \ldots, E \{P_N\} \), the variances \( V \{P_1\}, V \{P_2\}, \ldots, V \{P_N\} \), and covariance’s \( COV \{P_i, P_j\} \) [17] [18].

B. Overall ACOPF Formulation

Overall ACOPF formulation includes RHC based forecasted price that is used to allocate the DISCO retail optimization. At the DISCO level, the objective is to minimize the total cost including other DG’s, wind farm, and storage with wholesale market operating cost as the input. The constraints are the respective real and reactive powers for each resources, storage capacity and charge and discharge constraints of the battery. Equations (3)-(17) illustrates the overall formulation. Overall objective function, power flow equations, active and reactive power constraints, ramp rate for DG generation, system security limits and energy storage constraints are discussed next.

- Objective Function

The objective function tries to find optimal total hourly cost by utilizing economical generation at different hours subject to corresponding equations. Wholesale market price, neighboring DISCO price, operation cost for DGs and constant cost of the distribution system are included into objective function as the input parameters.
Min \[ \sum_{i=1}^{n} \sum_{t=1}^{24} (P_{DG,i,t} \times P_{DG,y,i}) + (P_{WF,i,t} \times P_{WF,y,i}) \\ + (P_{WM,i,t} \times P_{WM,y,i}) + (P_{ND,i,t} \times P_{ND,y,i}) + CC_{i,t} \] (3)

- **Power Flow Equations**

Active and reactive power generation and demand should meet the kirchhoff’s laws at each bus of the system. The power that is generated or purchased should be equal to the demand plus losses. These facts are included as constraints into formulation using following equations:

\[ P_{W,i,t} + P_{DG,i,t} + P_{WF,i,t} + P_{DS,i,t} - P_{CS,i,t} + P_{ND,i,t} - d_{i,t} = \sum_{j=1}^{n} |V_{i,t}| |V_{j,t}| |\delta_{i,j} - \delta_{i,t} + \theta_{i,j}| \] (4)

\[ Q_{W,i,t} + Q_{DG,i,t} + Q_{ND,i,t} - d_{i,t} = \sum_{j=1}^{n} |V_{i,t}| |V_{j,t}| |\sin(\delta_{i,j} - \delta_{i,t} + \theta_{i,j})| \] (5)

- **Active and Reactive Power Generation and Exchanged**

The active and reactive power generation and the power bought from the wholesale market or the power can be exchanged by neighboring DISCO cannot hit their respective upper and lower limits. This fact is illustrated using (6)-(7). The active and reactive power that can be purchased from wholesale market is limited and is positive at all times (8). This means that DISCO cannot sell energy to the wholesale market and its generation is very small compared to wholesale market capacity. Moreover, the power can be transferred between DISCO and its neighboring DISCO is limited based on the energy contract (9).

\[ P_{DG,i,t}^{min} \leq P_{DG,i,t} \leq P_{DG,i,t}^{max} \] (6)

\[ Q_{DG,i,t}^{min} \leq Q_{DG,i,t} \leq Q_{DG,i,t}^{max} \] (7)

\[ 0 \leq P_{WM,i,t} \leq P_{WM,i,t}^{max} \] (8)

\[ P_{ND,i,t}^{min} \leq P_{ND,i,t} \leq P_{ND,i,t}^{max} \] (9)

- **DG Generation Ramp Rate**

The ramp rate limits for each generating resources are illustrated using (10) and (11).

\[ P_{DG,i,t} - P_{DG,i,t+1} \leq RU P_{i,t} \] (10)

\[ P_{DG,i-1,t} - P_{DG,i,t} \leq RD_{N,i,t} \] (11)

- **System Security Limits**

Voltage security and thermal constraints are illustrated in (12) and (13).

\[ V_{i,t}^{min} \leq V_{i,t} \leq V_{i,t}^{max} \] (12)

\[ S_{ij,t} \leq |S_{ij,t}^{max}| \] (13)

- **Energy Storage constraints**

Energy storages are dynamic equipment in the power system. The amount of stored energy in storages are completely dependent on the previous state (14). In addition, each energy storage can store energy only at a specific level with specific charging and discharging rate. These constraints are illustrated in (14)-(17).

\[ E(i,t+1) = E(i,t) + P_{CS,i,t} \times \eta_{CS} - P_{DS,i,t} \times \eta_{DS} \] (14)

\[ E_{t,t}^{min} \leq E_{t,t} \leq E_{t,t}^{max} \] (15)

\[ 0 \leq P_{CS,i,t} \leq P_{CS,i,t}^{max} \] (16)

\[ 0 \leq P_{DS,i,t} \leq P_{DS,i,t}^{max} \] (17)

III. IMPLEMENTATION TEST SYSTEMS AND CASE STUDIES

A. RHC Price Forecasting

First the proposed RHC price prediction based on the real time price data is evaluated in this section. For evaluation, the wholesale market price is forecasted for next 24 hours using the previous hours real time price data from market. Generally, the number of previous hours real price data (N) is selected based on the required computational speed for developing the control variables. Here, the time step in RHC process is considered as 1 hour, and at every time step the previous 24 hours real price is deployed in RHC forecasting model (N=24) to forecast next 24 hour price. Table I depicts a the results of RHC forecast methodology for hours 1,4,8,12,16,20,24. For instance, the first row shows the forecasted price for hours 1 to 24 of next day using the real price data associated with hours 1 to 24 of current day. This process is repeated continuously during the system operation.

As shown in Table I, forecasted price for a specific hour is changing when the time step is moving towards that hour. For example, at step 1 the price prediction at hour 12 is based on the previous day data. However, at hour 11, for price prediction for hour 12, the real price data from hours 1 to 11 of current day and real price data from hour 12 to 24 from previous day is incorporated in stochastic RHC model. In the later case, the model produces more accurate forecast for hour 12.
Table I
PREDICTED PRICE FOR WHOLESALE MARKET USING RHC METHOD

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<th>Current Hour (Step)</th>
<th>Next Hours</th>
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<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
<th>20</th>
<th>24</th>
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shows the difference between RHC forecasting and one shot price forecasting. In this figure, base case shows the forecasted price for hour 1 to 24 of next day when we are at hour 24 of current day. On the other hand RHC prediction presents the most updated price forecasted one hour before this step using the most recent market price data. This example illustrates the need and effectiveness of the real-time pricing with RHC. In the next sections, this receding price prediction is deployed in optimization process for scheduling the power grid.

B. Test System 1: 3 Bus Test System

In order to illustrate the concept, first the proposed hybrid RHC based ACOPF algorithm is tested on a 3 bus simplified radial test system (Fig. 3). This test system consist of one substation which is connected to wholesale market, one DG unit and three loads. In the base case, the conventional ACOPF results show that the overall operational cost for the mentioned system is $1512.5. The operational cost is lower ($1485.7) utilizing RHC with energy storage which shows better system efficiency. The energy storage will be charged and discharged using real-time optimization to increase system’s social welfare. Figure 4 compares the storage capacity for the base case using price data for the next 24 hours with the proposed RHC based optimization. It can be seen that during peak hours, the storage charging capacity is dynamically changed with the proposed method compared to the base case.

C. Test System 2: 32 Bus Test System

In this section a 32-bus [19] radial test system is used for evaluating the proposed method. This system contains five DGs, two wind farm and one storage. The overall one line diagram is as shown in Fig. 6. Hourly load and wind power forecasted are taken from real-system data. It is assumed that ACOPF based on following methods:

Method 1: Base Case: Scheduling the grid based on price
Figure 4. Storage capacity using price data for the next 24 hours and proposed RHC.

Figure 5. Power exchanged between distribution network and neighboring DISCO.

Figure 6. Example 32 bus distribution system for analysis.

Method 2: RHC based Optimization: Scheduling the grid using RHC incorporating updated price prediction at every hour by using previous real price from market. Time horizon and time step are considered 24 hours and 1 hour respectively.

1) Power Exchange and Operating cost: First we evaluate the total power exchange. Figure 5 illustrates the total power exchanged between distribution network and neighboring DISCO. As it can be seen, in the base case, based on predicted price for wholesale market, system operator decide to mostly purchase power from neighboring disco during hour 8 to 24. However, based on RHC method at mentioned hours, based on wholesale market price the energy exchange between two neighboring DISCOs frequently changes. The system operator will buy the energy when energy price in the wholesale market is higher than DISCO’s price which is dependent on the real-time price forecasting and energy storage usage.

Figure 7 illustrates the operating cost for DISCO with and without the proposed method. As it can be seen, with the proposed architecture, system operation cost are mostly higher than base case during offpeak hours. However, during peak hours, the RHC based optimization shows better operating cost and margin. Subsequent storage capacity with and without RHC is illustrated in figure 8.

Figure 9 illustrates the energy storage usage with and without the proposed method. As it can be seen from this figure, the energy usage from hours 11-13 has been shifted to 17-19 based on the energy storage and real-time pricing obtained using RHC based optimization. Figure 10 illustrates
the power exchanged to and from the wholesale market. As it obvious, the system operator decided to buy less energy during peak hour due to increasing energy price in wholesale market. As the system energy price increase operator decide to buy energy from neighboring DISCO and/or utilizing the energy storage.

2) Overall Analysis: As it can be clearly seen from the previous discussions, the proposed approach shows better results with stochastic pricing in real-time for distribution system management with intermittent resources. The proposed method also allows to manage distributed storage in the presence of market interactions. The storage capacity is maximized and the power exchange is a result of overall wholesale market price and the neighboring DISCO price. This allows supply side elasticity and DER management. This approach can be further extended for demand elasticity and demand side management as well.

IV. CONCLUSION

In this paper a novel method for real-time optimization of power distribution network with storage is proposed. The proposed approach utilizes wholesale market price and the neighboring DISCO prices in the presence of DER and storage. The approach efficiently manages all assets including pricing. The uniqueness of the approach is that the RHC optimized real-time changes (in this case every hour) in pricing and energy dynamics and thus allows dynamic optimization with storage. Overall, the approach allows high controllable dynamic stochastic optimal power flow in distribution system.

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