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Power System Dynamic Scheduling with High Penetration of Renewable Sources

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Abstract— **In this paper, we present a model predictive control (MPC) based method for dynamic economic power scheduling in power grids. The proposed method is first applied to the power systems with relatively low penetration of renewable generation sources. The proposed MPC-based optimization method is then extended to the case, where a high penetration of renewable sources is expected. In the latter case, instead of considering power generated from renewable sources as a negative load, the system operator (SO) takes these sources into account as dispatchable in solving the scheduling problem. Various constraints pertinent to power systems including transmission congestion and generators' capacity are also considered in the optimization process. Consequently, we will show that the use of storage devices will be an effective way to reduce the cost of generation in the future generation of power systems. The effectiveness of the proposed power scheduling methods will be demonstrated using an IEEE 14-bus system combined with the California ISO data.**

I. Introduction

Scheduling problem in power systems is defined as *determining the outputs of power generation units to balance supply and demand considering the power network constraints*. In economic scheduling, an optimization problem is solved by system operator (SO) to minimize the generation cost. Utilizing concepts from control theory, dynamic economic scheduling (DES) was first introduced in 1970's [3], in which the demand prediction over a period of time was taken into consideration at each optimization step. Moreover, the method was shown to handle the ramp rate constraint of generators which is a *dynamic constraint* [18]. Obviously, DES can be more realistic and useful in long term compared to the solution obtained from a static economic scheduling problem [10], [19].

There have been several approaches proposed to address the DES problem. In [17], dynamic programming has been suggested for solving the optimization problem corresponding to DES. However, the computational time and dimension of scheduling problem based on dynamic programming would increase with the dimension of the power system. In 1980's, DES problem was transformed into the minimization of entire generation cost on a particular period of time interval, known as dynamic economic dispatch (DED) [20], [21]. Different methods were proposed to solve the DED problem including gradient projection method, Lagrange relaxation, *etc.* [6], [7]. Unfortunately, DED violates the ramp rate constraint of generation units [22]. More importantly, DED strategy is an open-loop control policy, and hence, there is no control over any deviation from the forecasted demand or any disturbance affecting the generation units' output.

Renewable energy sources affect the operation of the power systems. Intermittency and uncontrollability of these sources have made them different from traditional power generation sources from the operation point of view. Similar to the demand profile, renewable sources production should be predicted ahead of the operation. Power generation from renewable sources is currently counted as a small portion of supply; for instance, the estimated wind generation in the United States as a proportion of power consumption was less than 2.5% in 2010. Due to this low percentage, the most common approach in dealing with renewable production in power system operation is to consider them as a negative load; some examples can be found in [2], [8], [14]. On the other hand, the fossil fuels' price and the trend for reducing the carbon footprint are increasing. Due to these reasons, many countries have officially announced the plans to increase the renewable energy generations; United States, for instance, has targeted to raise its power generation from wind source to 20% by 2030 [13].

With an increase in the penetration of renewable sources in supplying power, the use of negative load approach will not be appropriate anymore. There are a number of reasons that prohibit SO from fully utilizing renewable generations. In [9], authors have illustrated that it is not efficient to dispatch the maximum capacity of renewable generations when 30% of the total power is provided by wind power. They have shown that by considering intermittent sources as dispatchable units, the efficiency of economic dispatching problem can be improved since they can increase the generation of cheap and slow-response units such as coal and nuclear power and decrease the generation of expensive but fast-response units such as gas power plants. This advantage arises from the almost cost-free generation and high ramp rate characteristics of renewable sources and in particular wind power.

Model predictive control (MPC) is a powerful control design method that uses a model to project the behavior of the system. Based on this model, controller can predict the future response of the system to various control actions and make an optimal decision based on this prediction. A complete description of the different MPC techniques along with the theoretical developments on MPC literature can be found in [5], [11], [12]. For problems such as power system scheduling which highly depends on the forecasted value of demand and renewable energy productions, this method is

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effective. In addition, due to its closed-loop nature, MPC can correct errors in the prediction of load and renewable generations in the next iteration and hence help to improve system stability and robustness [4], [15]. Other advantages of MPC in power system management have been discussed in [16].

In this paper, we examine the impact of high penetration of renewable generation sources on the future generation of power systems from different points of view. We will show that due to the constraints on capacity of the transmission lines, SO can no longer treat renewable sources as negative loads and dispatch their total power generated. Instead, we show that this issue can be handled by considering the renewable sources to be dispatchable units in the underlying optimization problem. In addition, we study the effect of integrating storage devices (and in particular batteries) with renewable sources in the DES problem. The use of storage devices will not only enable us to schedule the power from intermittent sources but also utilize their maximum capacity of production.

II. Power System Economic Scheduling: Problem Statement and Formulation

In power scheduling problem, SO's primary objective is to schedule the generators' output to reliably and efficiently supply power requested by the end users. This scheduling that aims to minimize the cost of generation should be implemented in a cost-efficient way. To this purpose, we first consider an objective function defined as

$$J := \sum_i C_i(G_i(t)), \tag{1}$$

where $C_i(G_i(t))$ is the cost function corresponding to the i^{th} generator at time instant t that depends on its generated power $G_i(t)$. The relation between the generator's output at time instants t and $t+1$ is described by the state equation

$$G_i(t+1) = G_i(t) + u_i(t), \tag{2}$$

where $G_i(t)$ is the system state and $u_i(t)$ is the generator ramp rate considered to be the system input. The objective function is often assumed to be affine or quadratic to ensure the convexity of the underlying problem.

A. Formulation of the Power System Constraints

First, we describe some of the typical constraints imposed on the power systems.

Constraint 1 (*Supply-demand constraint*): This limitation illustrates the balance of demand and supply at each time instant as

$$\sum_i G_i(t) = L(t), \tag{3}$$

where $L(t)$ is the total load at time instant t.

Constraint 2 (*Generators' capacity constraint*): This constraint can be mathematically formulated as

$$G_i^{min}(t) \le G_i(t) \le G_i^{max}(t). \tag{4}$$

For conventional suppliers such as coal and gas units, the minimum and maximum capacities, denoted respectively by $G_i^{min}(t)$ and $G_i^{min}(t)$, are constant; however, for renewable generation sources, these values change based on their forecasted profile.

Constraint 3 (*Ramp-rate constraint*): A substantial mechanical stress in the prime mover can be created due to over increasing or decreasing the output of generators. This immoderate stress can cause a serious long term harm to the unit and eventually leads to a shorter life span [10]. To avoid this, a dynamic constraint is imposed on the rate, at which a generator can increase or decrease its output as

$$\begin{aligned} G_i(t+1) - G_i(t) &\le R_i^u \\ G_i(t) - G_i(t+1) &\le R_i^d, \end{aligned} \tag{5}$$

in which R_i^u and R_i^d represent ramp-up and ramp-down limits, respectively.

Constraint 4 (*Transmission networks with capacity constraints*): This constraint is imposed due to the limitation of transmission lines and can be represented by

$$|F_{ij}(t)| \le F_{ij}^{max}, \tag{6}$$

where F_{ij} is the power transmitted through the line between buses i and j and is a function of power injected by contributing buses in the network, and F_{ij}^{max} is the maximum capacity of the transmission line between buses i and j. The relation between the lines' power vector denoted by $F(t)$ and buses' power vector denoted by $P(t)$ can be expressed as

$$P(t) = AF(t), \quad P \in R^N,\ F \in R^K \tag{7}$$

where N is the number of buses, K is the number of lines and A is a constant matrix. Notice that each element in vector $P(t)$ equals to generated power in the bus corresponding to that element minus its demand at time instant t. For instance, if bus i generates $G_i(t)$ and consumes $L_i(t)$, we have $P_i(t) = G_i(t) - L_i(t)$.

B. Formulation of the Dynamic Power Scheduling Problem

In this section, we describe the problems we will address in the paper. The first problem is *the scheduling problem with finite-capacity transmission network*. To pursue the discussion, we divide the power generators into two sets: (i) conventional generators such as coal and gas units represented by $\mathscr{C}$, and (ii) renewable generation sources such as wind and photovoltaic units represented by $\mathscr{R}$.

Problem 1.1 (*Renewable generation as fully dispatched resources*): Considering that renewable sources are treated as fully dispatched resources, hence acting like negative loads, the power scheduling problem can be addressed by solving the following optimization problem (for any $i \in \mathscr{C}$)

$$\begin{aligned} &\min_{u_i(t)|_{i\in\mathscr{C}}} J := \textstyle\sum_i C_i(G_i(t)) \\ &\text{subject to:} \\ &G_i(t+1) = G_i(t) + u_i(t), \\ &\textstyle\sum_{i\in\mathscr{C}} G_i(t) = L(t) - \sum_{i\in\mathscr{R}} G_i(t), \\ &G_i^{min}(t) \le G_i(t) \le G_i^{max}(t), \\ &G_i(t+1) - G_i(t) \le R_i^u, \\ &G_i(t) - G_i(t+1) \le R_i^d, \\ &|F(t)| \le F^{max}. \end{aligned} \tag{8}$$

Problem 1.2 (*Renewable generation as dispatchable resources*): Considering renewables as dispatchable generation sources, the power scheduling problem can be addressed by solving the following optimization problem (for any $i \in \mathscr{C} \cup \mathscr{R}$)

$$\begin{aligned} &\min_{u_i(t)} J := \textstyle\sum_i C_i(G_i(t)) \\ &\text{subject to:} \\ &G_i(t+1) = G_i(t) + u_i(t), \\ &\textstyle\sum_i G_i(t) = L(t), \\ &G_i^{min}(t) \leq G_i(t) \leq G_i^{max}(t), \\ &G_i(t+1) - G_i(t) \leq R_i^u, \\ &G_i(t) - G_i(t+1) \leq R_i^d, \\ &|F(t)| \leq F^{max}. \end{aligned} \tag{9}$$

It is noted that in Problem 1.2 (third constraint in (9)), maximum and minimum values corresponding to the renewable generations come from forecasted daily profile. The dependency of these upper and lower bounds on time is an implication of power variability from the renewable sources.

Remark 1: As described in Constraint 4*, the elements of power flow vector F, and hence the last constraint in (8) and (9), are dependent on the loads and power supplied from the contributing generation sources at each bus. Those inequalities then lead to the constraints that are dependent on the optimization variables.*

Remark 2: Assuming that there is no transmission loss and no restriction on the capacity of transmission lines, one can interpret that all the suppliers and consumers are connected to the same bus. In this case, scheduling problem with infinite-capacity transmission network *can be formulated similar to the ones described in Problem 1.1 and Problem 1.2 by removing the last constraint in (8) and (9).*

The last problem we address in this paper corresponds to the *integration of the renewable generation sources with storage devices*. To mathematically formulate the problem, we first describe the model we will use to represent the dynamics of the battery storage device. It is noted that the model considered here is a simple one that can capture the dominant characteristics of a battery. We use the following equation to describe the dynamics of the battery state of charge (SOC) for j^{th} battery (for $j \in \mathscr{R}$)

$$\begin{aligned} SOC_j(t+1) &= SOC_j(t) + \left(G_j^{max}(t) - G_j(t)\right)\eta_j \\ &- u_j^{dch}(t)(1/\eta_j), \end{aligned} \tag{10}$$

in which $SOC_j(t)$ is the state of charge at time instant t, $u_j^{dch}(t)$ is the discharged power that is injected to the grid and $G_j^{max}(t) - G_j(t)$ is the charging power that represents the undispatched portion of the power from the j^{th} renewable source, which would be stored. Finally, η_j is the round-trip efficiency of j^{th} battery, which we assume is split between charging and discharging. It should be noted that $SOC_j(t)$ (for all the batteries) will be augmented with $G_i(t)$ (for all the generation sources) to form a new state vector in the underlying optimization problem. Also, $u_j^{dch}(t)$ will be augmented with $u_i(t)$ to form the new vector of decision variables. The battery capacity is limited by

$$SOC_j^{min} \leq SOC_j(t) \leq SOC_j^{max}, \tag{11}$$

in which SOC_j^{min} and SOC_j^{max} denote minimum and maximum capacity, respectively. We note that the parameter SOC we consider here is not normalized, *i.e.*, per unit, and reflects the battery's available useful energy (in kWh).

Remark 3: There are two additional constraints on charge and discharge limits as

$$\begin{aligned} 0 &\leq G_j^{max}(t) - G_j(t) \leq P_j^{ch}\beta_j^c(t) \\ 0 &\leq u_j^{dch}(t) \leq P_j^{dch}\beta_j(t), \end{aligned} \tag{12}$$

in which P_j^{ch} and P_j^{dch} are maximum values on charge and discharge limits, respectively. In addition, in discharge mode, $\beta_j(t) = 1$, and in idle and charge modes, $\beta_j(t) = 0$. Also, in charge mode, we have $\beta_j^c(t) = 1$, and in idle and discharge modes, $\beta_j^c(t) = 0$. To avoid the battery charging and discharging at the same time, we impose an additional constraint as

$$\beta_j^c(t) + \beta_j(t) \leq 1. \tag{13}$$

The aforedescribed constraints should be checked to ensure that they always hold true.

Problem 2 (*Scheduling problem considering renewable generation as dispatchable resources, transmission line constraints and storage devices*): Considering storage devices integrated with the renewable sources, the DES problem can be addressed by solving the following optimization problem

$$\begin{aligned} &\min_{u_i(t)|_{i\in\mathscr{C}\cup\mathscr{R}},\ u_j^{dch}(t)|_{j\in\mathscr{R}}} J := \textstyle\sum_i C_i(G_i(t)) \\ &\text{subject to:} \\ &G_i(t+1) = G_i(t) + u_i(t), \\ &\textstyle\sum_{i\in\mathscr{C}\cup\mathscr{R}} G_i(t) + \sum_{j\in\mathscr{R}} u_j^{dch}(t) = L(t), \\ &G_i^{min}(t) \leq G_i(t) \leq G_i^{max}(t), \\ &G_i(t+1) - G_i(t) \leq R_i^u, \\ &G_i(t) - G_i(t+1) \leq R_i^d, \\ &|F(t)| \leq F^{max}, \\ &SOC_j(t+1) = SOC_j(t) + \left(G_j^{max}(t) - G_j(t)\right)\eta_j \\ &\qquad\qquad - u_j^{dch}(t)(1/\eta_j), \qquad j \in \mathscr{R} \\ &SOC_j^{min} \leq SOC_j(t) \leq SOC_j^{max}, \qquad j \in \mathscr{R}. \end{aligned} \tag{14}$$

III. Model Predictive Control and Corresponding Formulation for DES

MPC is a powerful control methodology, in which the behavior of a plant with a known model is predicted over a finite prediction horizon based on the latest measurements collected from the plant. Based on these measurements, MPC solves an optimization problem at each sampling time and calculates an input sequence, from which only the first one is implemented. We consider that the system is represented in terms of a difference equation by

$$x(t+1) = f(x(t), u(t)), \tag{15}$$

where $f(.)$ is *in general* a nonlinear function, $x(t) \in R^p$ is the state vector (with p elements) at time instant t, and $u(t) \in R^q$ is the control input vector (with q elements) at time instant t. For the DES problem under study in this paper, the system dynamics is described by a linear equation for each generator and each storage device. These equations represent the relation between generator outputs and battery SOC as described by (2) and (10), respectively. In addition, the states and control inputs are restricted to belong to a set that satisfies equality and inequality constrains corresponding to optimization problems introduced in Section II, *e.g.*, (14).

The MPC problem can be solved to ensure that the states of the controlled system converge to a reference trajectory by optimizing a performance index. For the DES problem under study in this paper, the control objective is to steer the generators' outputs to a demand profile while the constraints are met. We consider the performance index to be the power generation cost, which is assumed to be an affine function of the generation unit powers. The performance index is optimized at each prediction horizon step. Consequently, based on current information about generations' power and SOC of the storage devices, a control input sequence would be obtained that determines the generators' ramp rate and storage devices' output at each sampling time. Only the first sample of the control sequence is implemented as the input to the system difference equations (2) and (10) at time instant t to give the updated states at time instant $t+1$. This on-line calculation of optimal generators' output and storage devices' SOC is also referred to as *receding horizon scheduling*. For the simulation results shown in the next section, we have used MATLAB command *linprog* to solve the underlying optimization problems due to the linear nature of those problems.

IV. Numerical Examples

To examine the effectiveness of the proposed scheduling policy using MPC, we employ a 12-bus power network, which is modified from an IEEE 14-bus system [23] shown in Figure 1. Five-minute intervals of the forecasted total demand have been extracted based on the data from November 1st., 2011 provided in California ISO website [1]. This load profile is shown in Figure 2(a). In addition, 5-minute intervals prediction of the total renewable power consisting of wind and photovoltaic units generation is calculated based on California ISO data for the same day [1]. This profile is shown in Figure 2(b). Calculations from the data in Figure 2 show that, over the 24-hour period, the average amount of renewable production is 10.2% of the load average considering a balance in supply and demand. Table I shows the specifications of the power generation sources used in Figure 1 [9]. Based on the information provided above, we examine the dynamic power scheduling for different

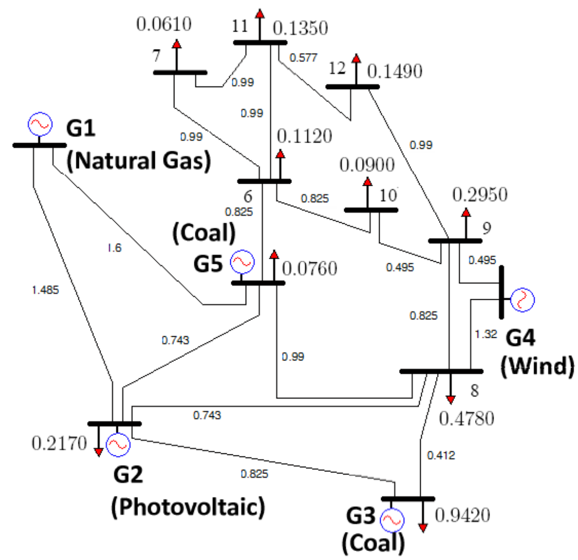

Fig. 1. Configuration of a 12-bus power network considering transmission line constraints and distributed loads (modified from [23])

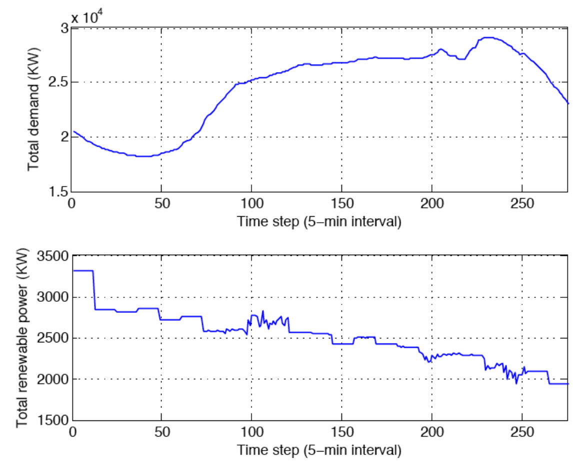

Fig. 2. (a) Total demand in KW, (b) Total renewable generation in KW

scenarios discussed in the previous section considering two cases, where the generation from the renewable sources is either 10% or 20% of the total power demand.

A. Considering 10% renewable generation with no transmission congestion

First, we consider that about 10% of the total power needed to ensure a balance in supply and demand comes from the renewable sources and that there is no limitation on transmission lines. To this purpose, we use the profiles shown in Figure 2. We discuss the results obtained by solving the optimization problems associated with the two power scheduling problems introduced in the previous section. Those two problems are solved using the MPC method considering renewable generations as negative load (Problem 1.1) or as dispatchable sources (Problem 1.2). Figure 3 demonstrates that both methods are capable of meeting the demand. The total cost of generation is also calculated and for both methods turns out to be the same and equals to $\$4.3822 \times 10^5$.

TABLE I

CHARACTERISTICS OF THE GENERATION SOURCES

Bus #	Type	Capacity (KW)	Marginal Cost ($/MWh)	Ramp-up (KW/5min)	Ramp-down (KW/5min)
1	Natural Gas	5000	130	150	180
2	PV	1000	10	100	120
3	Coal	10000	50	50	60
4	Wind	3000	10	180	220
5	Coal	9000	50	50	60

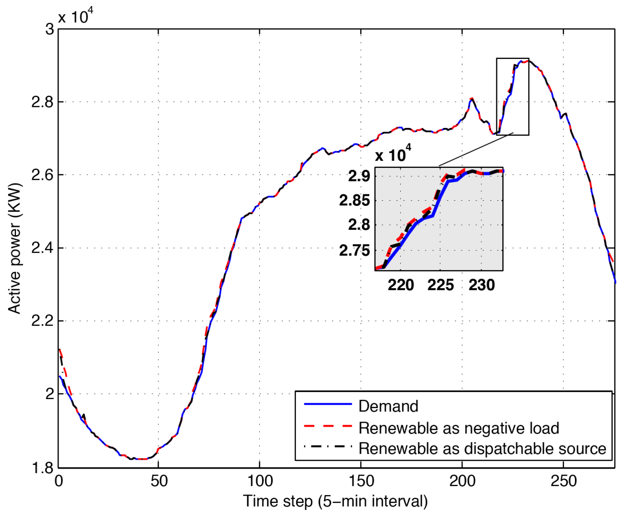

Fig. 3. Profiles of demand (solid line), total supply power considering renewable generation sources at buses 2 and 4 as negative loads (dashed line), and total supply power considering renewable generation sources to be dispatchable (dash-dotted line)

The total available renewable power, which is considered as negative load in Problem 1.1 and as dispatchable in Problem 1.2, is shown in Figure 4. As observed, the dispatched amount is almost equal to the total power when there is no constraint on transmission lines.

B. Considering 20% renewable generation with transmission congestion constraint

Next, we investigate the effect of transmission line constraints on power scheduling problem in the presence of a higher penetration of renewable sources among electricity providers. To this purpose, we assume a distribution of the total load among buses. The configuration we study in this example is shown in Figure 1. It should be noted that all the values shown in the figure are in per unit (pu). We first show the details for representing the transmission line constraint in terms of the optimization variables. Considering bus 2, the second row of equation (7) becomes

$$P_2(t) = F_{21}(t) + F_{23}(t) + F_{25}(t) + F_{28}(t) \qquad (16)$$

based on Figure 1. It is noted that we also have $P_2(t) = G_2(t) - L_2(t)$. Next, we assume that 20% of the demand is supplied using renewable sources. To this purpose, we double the renewable generation numbers shown in Figure 2(b).

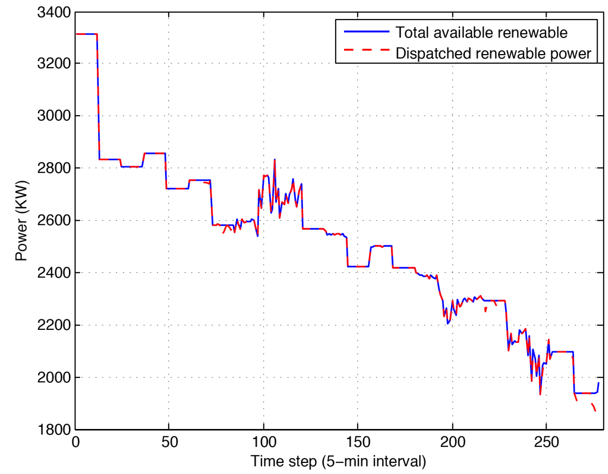

Fig. 4. Total available and dispatched amount of renewable power

Considering the transmission line constraints, we solve MPC problems corresponding to problems 1.1 and 1.2. Because of violating the transmission constraints, Problem 1.1 *does not provide a feasible solution*, and hence we would not be able to consume the total available renewable generations at each time instant when they are considered as a negative load. On the other hand, Problem 1.2 gives a feasible solution, implying that treating renewable generators as dispatchable sources can successfully handle the transmission constraints and schedule the available sources to supply the requested power.

Figure 5 illustrates the amount of power from renewable sources that is dispatched from the total available renewable power. This figure clearly shows the effect of transmission line capacity constraint on scheduling the renewable generations. It is inferred that a portion of available renewable generations cannot be scheduled due to the transmission line limits. The total cost of generation in this case is calculated to be $\$4.0217 \times 10^5$. It is noted that if we could fully dispatch renewable generations, the total cost would have been $\$3.7591 \times 10^5$.

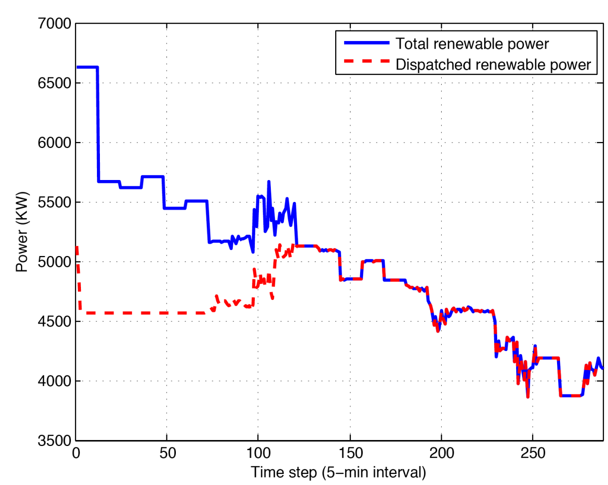

Fig. 5. Total available and dispatched amount of renewable generation

To avoid the loss of undispatched power from the renewable sources, we use storage devices at buses, in which there are renewable resources installed. We assumed a round-trip efficiency of 90% for the batteries, which is split between charging (95%) and discharging (95%), and charging and discharging rates of 250 KW/5-min and 300 KW/5-min, respectively. This approach has been formulated in Problem 2. In Figure 6, we have shown three profiles. Solid line shows the 24-hour total power available from the renewable sources generated at bus numbers 2 (photovoltaic) and 4 (wind). Dashed line shows the amount of dispatched renewable power. Due to the transmission congestion limits, the dispatched renewable power is lower than the maximum power available during the time between midnight and around 10 AM. Therefore, the difference between these two profiles is scheduled to be saved in storage devices. After 10 AM, transmission capacity allows system operator to dispatch not only the maximum available renewable power but also the stored power in storage devices. The total dispatched power from renewables and battery outputs is shown by the dash-dotted line. As observed, this profile is higher than the maximum generation of renewables. The accumulated difference between these two profiles is slightly less than the amount of power stored in batteries before 10 AM.

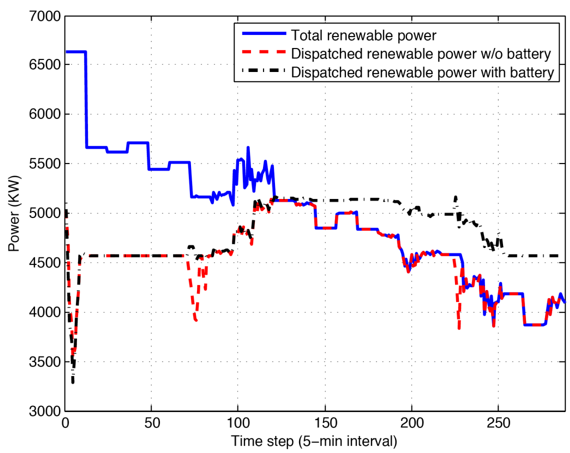

Fig. 6. Total available and dispatched amount of power from renewable sources with and without storage devices

We finally summarize the simulation results obtained by solving the DES using Problem 2. We showed that when there is a constraint on transmission lines, by utilizing the storage devices, unscheduled renewable power can be stored and later dispatched as shown in Figure 6. The adopted strategy in using storage devices reduces the generation cost from $\$4.0217 \times 10^5$ to $\$3.9288 \times 10^5$, implying an approximately 2.3% reduction in cost of generation.

V. CONCLUDING REMARKS

In this paper, we investigated various power scheduling strategies adopted to handle the high penetration of renewable generation sources among energy suppliers. To implement these power scheduling policies, we proposed to use MPC as a powerful solution method to solve the underlying optimization problems. The primary reason to employ MPC was its ability to: (i) handle both static constraints such as generators capacity and dynamic constraints such as generators' ramping rates, and (ii) correct any potential error in forecasting renewable generation due to its closed-loop nature and control law adaptation at different prediction horizons.

REFERENCES

[1] http://oasis.caiso.com/mrtu-oasis/?doframe=true&serverurl=http.

[2] S.J. Ahn and S.I. Moon. Economic scheduling of distributed generators in a microgrid considering various constraints. In *Proc. IEEE Power & Energy Society General Meeting, 2009*, pages 1–6, 2009.

[3] T.E. Bechert and H.G. Kwatny. On the optimal dynamic dispatch of real power. *Power Apparatus and Systems, IEEE Transactions on*, (3):889–898, 1972.

[4] R. Findeisen, L. Imsland, F. Allgower, and B.A. Foss. State and output feedback nonlinear model predictive control: An overview. *European Journal of Control*, 9(2-3):190–206, 2003.

[5] C.E. Garcia, D.M. Prett, and M. Morari. Model predictive control: Theory and practice–a survey. *Automatica*, 25(3):335–348, 1989.

[6] G. Granelli, P. Marannino, M. Montagna, and A. Silvestri. Fast and efficient gradient projection algorithm for dynamic generation dispatching. In *Generation, Transmission and Distribution, IEE Proceedings C*, volume 136, pages 295–302. IET, 1989.

[7] KS Hindi and M. Ab Ghani. Dynamic economic dispatch for large scale power systems: a Lagrangian relaxation approach. *International Journal of Electrical Power & Energy Systems*, 13(1):51–56, 1991.

[8] A. Hooshmand, M. Poursaeidi, J. Mohammadpour, and H. Malki. Stochastic model predictive control method for microgrid management. In *Proc. IEEE Conference on Innovative Smart Grid Technologies*, 2012.

[9] M. Ilic, L. Xie, and J.Y. Joo. Efficient coordination of wind power and price-responsive demand- part I: Theoretical foundations. *Power Systems, IEEE Transactions on*, (99):1–1, 2010.

[10] D.S. Kirschen, G. Strbac, and Inc Ebrary. *Fundamentals of power system economics*. Wiley Online Library, 2004.

[11] J. Lee and Z. Yu. Worst-case formulations of model predictive control for systems with bounded parameters. *Automatica*, 33(5):763–781, 1997.

[12] J.H. Lee, M. Morari, and C.E. Garcia. State-space interpretation of model predictive control. *Automatica*, 30(4):707–717, 1994.

[13] S. Lindenberg. *20% Wind Energy By 2030: Increasing Wind Energy's Contribution to US Electricity Supply*. DIANE Publishing, 2009.

[14] T. Namerikawa, T. Hatanaka and M. Fujita. On predictive control for systems with information structured constraints. *SICE Journal of Control, Measurement, and System Integration*, 1(1):1–8, Jan. 2010.

[15] G. Nicolao, L. Magni, and R. Scattolini. Stability and robustness of nonlinear receding horizon control. *Nonlinear model predictive control*, pages 3–22, 2000.

[16] B. Otomega, A. Marinakis, M. Glavic, and T. Van Cutsem. Model predictive control to alleviate thermal overloads. *Power Systems, IEEE Transactions on*, 22(3):1384–1385, 2007.

[17] D.W. Ross and S. Kim. Dynamic economic dispatch of generation. *Power Apparatus and Systems, IEEE Transactions on*, (6):2060–2068, 1980.

[18] C. Wang and S. Shahidehpour. Optimal generation scheduling with ramping costs. In *Proc. IEEE Power Industry Computer Application Conference*, pages 11–17, 1993.

[19] A.J. Wood and B.F. Wollenberg. *Power generation, operation, and control*, volume 2. Wiley New York, 1996.

[20] W. Wood. Spinning reserve constrained static and dynamic economic dispatch. *Power Apparatus and Systems, IEEE Transactions on*, (2):381–388, 1982.

[21] X. Xia and A. Elaiw. Optimal dynamic economic dispatch of generation: A review. *Electric Power Systems Research*, 80(8):975–986, 2010.

[22] X. Xia, J. Zhang, and A. Elaiw. An application of model predictive control to the dynamic economic dispatch of power generation. *Control Engineering Practice*, 2011.

[23] L. Xie and M. Ilic. Model predictive economic/environmental dispatch of power systems with intermittent resources. In *Proc. IEEE Power & Energy Society General Meeting*, pages 1–6, 2009.