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MPC-based approach for online demand side and storage system management in market based wind integrated power systems

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ABSTRACT

Ever-increasing rate of wind power generation as an uncertain and variable source of energy, face new challenges in power system operation. For this reason, optimal real-time operation of wind integrated power systems in profit based markets considering the effects of probabilistic future variations of wind speed is one of the main concerns of system operators. For this purpose, some solutions such as demand response (DR) programs and energy storage systems (ESS) are widely being used to cover and manage wind generation uncertainty. But some of them such as DR programs can add some extra sources of uncertainty due to unpredictable customer's behavior. To this end, this paper proposes an online model-based predictive control approach for optimal real-time operation of wind integrated power systems including DR and ESS facilities. Discrete-time manner, re-optimization characteristic, and adaptability are the main features of the proposed MPC method which make it well-suited to address high uncertainties regarding wind power generation and customer's behavior. Besides, MPC considers all interactive effects of the control facilities in accordance with the expected wind farm output power in the future prediction horizon to maximize wind power utilization and so enhance social welfare. In addition, the uncertain nature of wind power is modeled using Markov chain Monte Carlo method. For efficiency evaluation of the proposed approach, simulation is implemented in MATLAB software using YALMIP optimization toolbox for the 8-bus test system. Results confirm the acceptable performance of the proposed approach in reducing operation cost through optimal uncertainties management.

1. Introduction

Wind power as a clean and sustainable source of energy is in the center of concentration and is expected to supply 15% of the total demand by 2025 in the world [1]. Obviously, wind power variation and uncertain nature, affects operation decisions in market-based power systems. In other words, optimal operation of high penetrated wind integrated power systems requires more flexible control facilities as well as more adaptive control approaches to maximize benefits from wind farms while alleviating negative impacts of wind speed uncertainty [2]. Thus, selection of the most effective control facilities, besides the efficient control techniques can maximize wind power utilization and consequently enhance social welfare. In this regard, energy storage systems (ESS) and demand response (DR) programs, as two fast response and flexible control facilities, have attracted considerable attention for optimal wind power uncertainty management. In recent years widespread research has been carried out in this context using various control methods and optimization approaches.

ESSs are so beneficial for power systems with high wind power penetration. Wind farms energy time-shifting, mitigating wind power forecasting errors, relieving transmission bottlenecks and frequency control issues are some of these facilitations which can result in more efficient integration plans of wind energy [3]. In [4] the effects of intermittent wind generation on smart distribution companies in day-ahead markets has been analyzed considering storage systems and electric vehicles as fixed and mobile loads, respectively. In [5] wind uncertainty impact on the ESS and thermal units operation plans is studied by a stochastic unit commitment (UC) model. For this purpose, minimization of the daily operation cost as a stochastic mixed integer linear program has been implemented using GAMS software. Ref. [6] proposes the use of ESS facility for optimizing cost, emission, and the uncertain wind power penetration level in a dynamic economic emission dispatch model. The utilization of ESS systems for covering the wind power prediction errors is the main contribution of [7]. The optimal output power and capacity of ESS has been determined in [8] with the aim of wind power curtailment minimization. For this purpose, a two-stage method is developed to optimize wind farms output power and schedule thermal generators commitment. Thereafter, ESS design

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Nomenclature

Sets and indices

T	set of time intervals
Ω_D	set of load buses
Ω_b	set of buses
Ω_{DR}	set of demand response load points
Ω_L	set of transmission lines
Ω_L^i	set of lines connected to bus i
Ω_G	set of conventional generators.
Ω_W	set of wind farms
Ω_S	set of ESS units
DT	Deadline Time
N_p	prediction horizon
N_c	control horizon
p_{jk}	transition probability of moving from the initial state j to final state k
X_t	wind state at time t
$P(S)$	transition probability matrix
P	nominal output power of wind farm
M_t	transition matrix
$P_{D_{i,t}}$	active load of bus i at time t
$P_{DR_{i,t}}$	total demand response of bus i at time t
$P_{DLCDR_{i,t}}$	direct load control of bus i at time t
$P_{LSDR_{i,t}}$	total shiftable load of bus i at time t
$\delta_{i,t}$	coefficient of flexible load supply
$S_{i,t}$	stored energy of the i-th ESS unit
η_i^{ch}	charging efficiency of the i-th ESS unit
η_i^{disch}	discharging efficiency of the i-th ESS unit
$P_{G_{i,t}}$, $P_{W_{i,t}}$, $P_{ESS_{i,t}}$	output power of the i-th thermal units, wind farm, and ESS at time t
$P_{ESS_{i,t}}^{\max}$	power rating of the i-th ESS unit
$SOC_{initial}$	initial SOC of the ESS unit
Q	ESS capacity
$SOC_{ESS_{i,t}}$	state of charge of the i-th ESS at time t
$SOC_{ESS_i}^{\min}$, $SOC_{ESS_i}^{\max}$	minimum and maximum SOC of the i-th ESS
N_b	number of buses
C_{DLCDR}	direct load control program cost
C_{LSDR}	load shifting program cost
$B(P)$	consumers' benefits
$C(P)$	power generation cost of thermal units
a_i, b_i, c_i	cost coefficients for the i-th generator
δ_n, δ_m	voltage angle at bus n and m
y_{nm}	element nm of the admittance matrix
θ_n, θ_m	angles of bus i and j
P_i	net power injection of bus i
$F_{nm}^{\max}$	thermal limit of the line n to m
π_i	lagrange multiplier of equality constraint for the i-th generator
τ_{nm}	lagrange multiplier of inequality constraint for line nm
$LMP_{i,t}$	LMP of the bus i at time t
$LMP_{i,t}^{energy}$	LMP of the bus i at time t related to energy cost
$LMP_{i,t}^{congestion}$	LMP of the bus i at time t due to congestion
$GSF_{nm,i}$	generation shift factor of line n to m
$P_{G_i}^{\min}$, $P_{G_i}^{\max}$	minimum and maximum power of the i-th generator
$P_{W_i}^{\max}$	maximum power rate of the i-th wind farm
$f_{nm,t}$	power flow of line nm

has been taken into account to determine its operational procedure. Ref. [9] investigates the UC problem considering a coordinated wind-pump storage hydro-thermal model. To this end, a non-linear utility function is developed to model the operation cost and load shedding. It is seen that the proposed approach is considerably able to follow the risk of decision making. Another research proposes an innovative integrated scheme to mitigate wind power uncertainty for solving the stochastic security constrained unit commitment (SSCUC) problem [10]. In this regard, transmission switching, demand response, and energy storage systems are introduced to form an integrated control plan as a mixed-integer linear programming formulation.

As mentioned, DR technique is the other capable solution, which has been used to mitigate the effects of wind power uncertainty and variation in power system operation. In short, DR is an effective approach to enhance the flexibility of power system operation and assist the operator to maintain the expected features at the acceptable range [11]. Refs. [12–14], investigates the related wind power uncertainty and tries to mitigate this effect using DR technique. Ref. [15] has chosen load reduction as DR program for wind power integration in a day-ahead energy market. Ref. [16] has proposed the use of DR, gas turbine, or storage for wind forecast error mitigation in 10 min market dispatch. Economic aspects of DR as an effective approach for wind power forecast error compensation has been proposed in [17]. Another research has studied the impacts of time sequence features of wind power forecast error in a day-ahead unit commitment problem [18]. To this end, the optimization of the UC model is implemented using the forecast error and reserve decision. The model is formulated as a mixed-integer nonlinear program. It is seen that the proposed model has improved the economical aspects of power system operation through balancing the costs of fuel, load shedding, and wind power curtailment risk.

Another study which analyzes dynamic economic dispatch, suggests DR program to facilitate the effects of high wind power penetration on the operation cost [19]. In [20], a novel active robust optimization dispatch model has been utilized to detect the related effects of hourly price DR in a day-ahead market. In this regard, all wind power generation conditions on IEEE 30 and 118-bus are evaluated and results show the flexibility of the mentioned optimization method in economic and secure wind integrated power system operation. In [21], DR resources optimal size and site have been determined in a transmission-constrained system considering wind power location.

It should be noted that optimal applicable scheduling of ESSs and some of the DR programs, such as load shifting, need time-dependent control approaches due to their operational constraints. In other words, optimal operation of these facilities in the current time interval, need some information about state and inputs of the system in future. Also, in future smart grids, some of these facilities such as DR programs are needed to be updated in short time intervals which in this case add extra uncertainties due to customer's behaviors. So, using these facilities are not sufficient lonely and implementation of an online, adaptive and updatable control approach is required to effectively manage the uncertainties and maximize wind power utilization and consequently enhance social welfare in power system operation plans.

Recently, model-based predictive control (MPC) has attracted the power system researchers attention. In fact, the abilities of future prediction, quick processing capacity, and suitability for multivariable control operations, make MPC a proper choice for power system operators. Furthermore, directly incorporation of constraints to objective function brings up MPC as a perfect real-time control approach [22]. In [23], load frequency control of a four area interconnected power system with wind farms is investigated using distributed-MPC (DMPC). Energy flow in distribution substations to achieve a more controllable power flow is studied in [24] using MPC. In this ref, the energy storage system is controlled considering the fluctuations of distributed energy resources. Another research is presented in [25], where a novel economic robust predictive controller is proposed to control multi microgrids. In

[22], the author proposes swarm-MPC (SMPC) for optimal operation of power system. This paper analyzes unit commitment/economic dispatch problem in presence of wind farms. A multi-stage predictive control approach with the feedback mechanism for compensation of demand and wind generation forecast error has been proposed in [26]. As stated in this paper, reformulating the problem as a finite moving-horizon optimal control problem decelerates the growth of the number of scenarios. Besides, using this approach decreases the computation time as uncertainties are gradually realized by updating the system. The conceptual structure of a rolling horizon UC with multiple periodicities is formulated in [27]. This paper proposes to solve the UC problem repeatedly based on the online and updated load, generation, and renewable production data considering the uncertain condition. The proposed framework allows for evaluation of different periodicities of the rolling horizon problem and brings more accurate forecasting information for the UC problem. A forecast-based predictive energy management, control, and communication system (PEMCCS) has been proposed and studied in a grid-tied wind energy conversion system with battery energy storage systems [28]. The PEMCCS model not only increases the revenue of the wind power producers but also minimizes the curtailment of wind energy conversion system and improves grid reliability, as well.

According to the literature review, some of the researchers have investigated the optimal operation of wind integrated power systems considering DR and ESS facilities. But the importance of looking ahead for optimal coordination of these facilities is neglected. Moreover, the application of predictive control and moving horizon approach for covering wind uncertainty has been implemented in some other papers. But, it is worth mentioning to point that there is no effort for looking forward in wind farm operation considering DR and ESS facilities and the effects of using them to manage non-predictable future of wind speed in real time decisions. Therefore, it's essential to take a new look in wind farms optimal operation considering DR and ESS facilities. This issue is more important where the control facilities (ESS/DR) are time-dependent and their optimal coordination in the current time interval is actually affected by future system condition. This outlook is required because of the time dependency of related control facilities as well as the variable and non-predictable behavior of future system condition. In other words, the predictive control of DR and ESS facilities for the optimal operation of wind farms in a prediction horizon considering the interactive dependence of control decisions has not been taken into consideration.

With this end in view, this paper proposes Model Predictive Control (MPC) plan in a real-time manner named online MPC-based algorithm to systematically coordinate the DR programs and ESS operation in market-based wind integrated power systems. Discrete-time manner, re-optimization characteristic, and signal tracking make it technically suited to address high uncertainties of wind power generation and customer's behaviors [29]. In fact, by employing the proposed approach the ESS operation and coordination of DR programs would be adjusted systematically in a way to reduce the cost of generation and consequently improve social welfare, effectively. Further, Markov-Chain Monte-Carlo (MCMC) method is used in this paper to model the stochastic behavior of wind power generation as a basis to evaluate the robustness and adaptability of the proposed method.

These features of the current paper distinguish it from existing papers in this area. Consequently, the particular contributions and novelty of the present paper are as follows:

- Providing an intelligent, adaptive, optimal and scalable method (MPC) to automatically cover online coordination of DR and ESS facilities in a market-based wind integrated power system while avoiding violation of the network constraints and respecting DR users' preferences.
- Taking the impacts of time dependency and constraints of combined DR and ESS facilities into account on optimal wind farms operation in power market
- Utilizing MCMC for modeling wind power generation with the purpose of revealing the impacts of the uncertain and variable source of energy in a coherent, coordinated manner to properly evaluate the robustness and adaptability of the proposed method.
- Maximizing social welfare in market-based wind integrated power system through optimal coordination of DR programs ESS operation with wind power generation.

The remaining of the paper is organized as follows. Section 2, first, describes MCMC methodology to model wind generation and then elaborates problem formulation and details proposed MPC for DR and ESS coordination. The test system configuration under study has been introduced in Section 3. In Section 4, results in the light of various scenarios are drawn and the outputs from MPC would be compared with the ones using a traditional single step approach. Finally, conclusions are presented.

2. Proposed MPC modeling structures and methodology

Towards fulfilling customer satisfaction, preventing grid technical violation, and minimizing total operation cost, MPC is presented for coordination of DR programs and ESS operation with wind power generation. For this purpose, first, a description of MCMC which is supposed to model the stochastic behavior of wind power generation is presented. Second, the control facilities model (DR and ESS) and problem formulation are presented and then, the proposed MPC methodology is presented.

2.1. Wind generation modeling using MCMC methodology

In this study, a predictive control strategy based on the MPC approach is suggested to optimize the operation procedure of a market-based wind integrated power system. Therefore, there is a mandatory need to forecast and estimate the future wind power generations to provide the controller with the required data for processing. To this end, the MCMC approach is employed to forecast wind power generations in the prediction horizon. It should be noted that in the practical implementation of the proposed MPC approach, the algorithm uses wind speed prediction data from the meteorological forecast. But here Monte-Carlo Markov-Chain (MCMC) method is used for wind speed and so wind power generation uncertainty modeling.

Markov chain is a stochastic process in which the present status is quite independent of past or future ones [30]. This is a series of events which is characterized by transition probabilities from j to k, that is:

$$p_{jk}(t) = \mathrm{P}(X_{t+1} = k \mid X_t = j) \tag{1}$$

Transition matrix also termed the transition probability matrix, involve the transition probabilities of passing between the Markov states. In fact, Transition probabilities are a function of occurrence s at a given time. For calculation of the element p_{ij} in the transition matrix, the number of transitions from the state S_i to S_j should be divided into the total number of S_i occurrences. With this end in view, each row of the transition matrix represents the current state of the process and the next possible states are stated in each column. Meanwhile, determining the transition matrix requires the historical wind speed data to be statistically analyzed. Therefore, the transition probability matrix is as follows:

$$P(S) = \begin{pmatrix} p_{11}(s) & p_{12}(s) & \cdots & p_{1n}(s) \\ p_{21}(s) & p_{22}(s) & \cdots & p_{2n}(s) \\ \vdots & \vdots & \ddots & \ddots \\ p_{n1}(s) & p_{n2}(s) & \cdots & p_{nn}(s) \end{pmatrix} \tag{2}$$

where sum of the elements at each row is equal to 1.

$$p_{jj}(s) = 1 - \sum_{i=1, i\neq j}^{n} p_{ji} \tag{3}$$

In this study, discrete-time and inhomogeneous type of Markov chain have been used. Thus, the simulation framework for modeling wind power generation consists of three steps:

(1) *Describing different states of Markov chain,*
(2) *Determining initial states and transition probabilities,*
(3) *Monte Carlo sampling (MCMC simulation),*

Accordingly, in this paper, five distinctive states for the wind farm output power is considered and it is assumed that, at each time interval, one and only one state from a set of states can take place for each wind site. Therefore, these five states corresponding to each wind farm generation are "P", "4/5P", "3/5P", "2/5P", and "1/5P", which P is the nominal power output of the wind farm. It's worth mentioning that, determining the number of states is a statistical-based analysis which is quite dependent on the geographical and climatic condition of the windy region. As a matter of fact, choosing the appropriate number of the Markov chain states requires a statistical analysis of wind speed historical data, which is certainly different for each location.

The time step for wind generation scenarios based on probabilities is chosen to be 1 h. The time horizon is selected for one day, albeit, depending upon the purpose of study it can be extended on a weekly, monthly, or yearly basis. It should be noted that there is no need to update the transition matrix in each time interval in daily basis studies, considering no severe weather changes during a day. But it is inevitable to use different transition matrices for different weather conditions (for example for each season) in yearly basis studies.

In the MCMC approach, first, the status of wind farm at $t = 0$ is defined. Then, future states of wind power generation are calculated using conditional probability matrix. Conditional probability for a specific wind farm at time t, (for $t \in [0, 24]$), passes to S_K is shown by $p^t_{j\to k}$ provided that at the moment before was in $S_j (j = 1, 2, 3, 4, 5)$.

$$p^t_{j\to k} = P(S^t_K \mid S^{t-1}_j) \tag{4}$$

Therefore, for a given t, the transition matrix is defined as follows:

$$M_t = \begin{bmatrix} p^t_{1\to1} & p^t_{1\to2} & p^t_{1\to3} & p^t_{1\to4} & p^t_{1\to5} \\ p^t_{2\to1} & p^t_{2\to2} & p^t_{2\to3} & p^t_{2\to4} & p^t_{2\to5} \\ p^t_{3\to1} & p^t_{3\to2} & p^t_{3\to3} & p^t_{3\to4} & p^t_{3\to5} \\ p^t_{4\to1} & p^t_{4\to2} & p^t_{4\to3} & p^t_{4\to4} & p^t_{4\to5} \\ p^t_{5\to1} & p^t_{5\to2} & p^t_{5\to3} & p^t_{5\to4} & p^t_{5\to5} \end{bmatrix} \tag{5}$$

$$P\left[\sum\nolimits_k S^t_K \mid S^{t-1}_j\right] = \sum\nolimits_k p^t_{j\to k} = 1 \tag{6}$$

The general structure of the Markov chain formed in this study is shown in Fig. 1. In which only the transition possibilities from state three to others are depicted for more clarity.

2.2. Control facilities model

In this section, the both fast response DR and ESS control facilities are modeled and discussed considering their technical constraints.

2.2.1. DR programs

In this paper, two types of demand response programs including direct load control (DLC) and load shifting (LS) are considered. It's worth mentioning that the DLC and LS are involuntary and voluntary DR programs respectively. In other words, in DLC program, there is no effective participation between the system operator and customers. On the contrary, in LS, customers themselves participate in DR program.

DLC or load shedding programs are implemented whenever the technical constraints are violating or even the load is not economically profitable to be supplied. Moreover, the corresponding cost of load shedding must be a high-cost value not to permit the operator to interrupt customers demand occasionally. Besides, LS is the other DR program that increases power system flexibility through shifting the flexible demand. In fact, LS is a load management technique which permits the operator to shift the demand to off-peak hours. Indeed, LS programs are performed whenever it is possible to shift load to future time intervals. To do so, customers of each bus announce the amount of their required energy and the corresponding deadline that should be supplied. In other words, in each time interval, the end-users ask for the specified amount of energy which should be supplied in a certain duration of time. But, the exact time of supply is not important and the system operator is able to shift their required energy provided that it is supplied at the appointed deadline. In fact, the maximum possible time interval for shifting a specific load is equal to its deadline time and the operator is obligated to supply the shifted loads until its deadline time. So, the two types of considered DR program can be formulated as below:

$$P_{DR_{i,t}} = P_{DLCDR_{i,t}} + \delta_{i,t} P_{LSDR_{i,t}} \qquad \forall\, i \in \Omega_{DR},\ \forall\, t \in T \tag{7}$$

In this equation, $P_{DR_{i,t}}$ represents the total demand not supplied which is exactly because of executing both load shedding and load shifting programs in each time interval. The equation is comprised of two different parts of $P_{DLCDR_{i,t}}$ and $P_{LSDR_{i,t}}$, which represent the amount of load shedding and load shifting of each time interval respectively. As a matter of fact, due to the possibility of performing DR programs, the operator is authorized to perform the load shedding and load shifting plans in each time interval.

Furthermore, the key important parameter in this equation is $\delta_{i,t}$ which shows the coefficient of flexible load supply. $\delta_{i,t}$ is a continuous number varying from "0 "to "1" which determines the portion of the flexible load i that is not going to be supplied in time interval t (shifted to future time intervals). Thus, $\delta_{i,t} = 1$ means that the total amount of shiftable load is shifted to future time intervals, while, $\delta_{i,t} = 0$ represent no load shifting has performed in the current time interval. The notable point is that the sum of the scheduled values of $\delta_{i,t}$ must be equal to 1 for each load point within its corresponding deadline time. This fact implies that the operator must schedule the amount of flexible load in such a way to guarantee the supply of the whole demand during its deadline time. This issue is specified in the following equation:

$$\sum_{t\in DT_{i,t}} \delta_{i,t} = 1 \qquad \forall\, i \in \Omega_{DR} \tag{8}$$

It's worth mentioning to point that the corresponding cost of load shedding program is assumed to be 45($/MWh) which is higher than the most expensive generator in the test system under study. This means that each MW load shedding in an hourly time interval imposes 45$ on the operation cost. Also, it should be noted that the corresponding cost of load shifting is a low-cost value equal to 0.1($/MWh). So, the operator does not pay a remarkable reward to the customers for participating in LS program. As a matter of fact, the accurate calculation of the customer's participation payment depends on different parameters including the amount of shifted load, the supply deadline time, and peak or off-peak shifting time. In practical, a fraction of revenue from performing LS program can be also rewarded to the customers to motivate them for more effective participation in this program. In summary, LS is

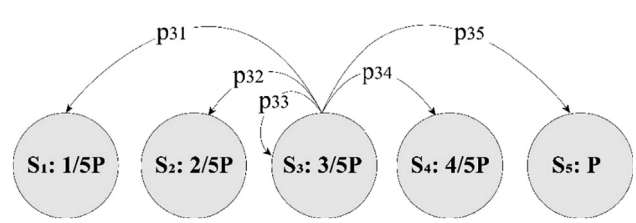

Fig. 1. Discrete-time and inhomogeneous Markov chain.

an incentive based DR program aiming to enhance social welfare which is a favorable factor in power system operation for both of the customers and the operator.

2.2.2. Energy storage system

Energy storage systems are a kind of responsive facilities, which has been taken into consideration for wind uncertainty mitigation recently. In fact, the effective performance of ESS is related to the ability of wind energy shifting and forecast error mitigation. Therefore, they are being widely used in wind integrated power systems.

At each time, the amount of stored energy in the ESS units can be calculated as below [31,32]:

$$S_{i,t} = \begin{cases} S_{i,t-1} - \eta_i^{ch} P_{ESS_{i,t}} & \forall\ i \in \Omega_S,\ \forall\ t \in T,\ if\ \ P_{ESS_{i,t}} < 0 \\ S_{i,t-1} - \frac{1}{\eta_i^{disch}} P_{ESS_{i,t}} & \forall\ i \in \Omega_S,\ \forall\ t \in T,\ if\ \ P_{ESS_{i,t}} \geqslant 0 \end{cases} \tag{9}$$

In the above equation, charging/discharging efficiency are two major technical factors in practical utilization of the ESS. Generally, the battery energy storage systems are highly efficient. In fact, the charging efficiency is high and due to small discharge loss of the ESS, discharge efficiency has assumed to be one [33]. Furthermore, The actual SOC in each time interval is calculated using Eq. (10) which is the ratio of the stored energy to the ESS capacity.

$$SOC_{i,t} = \frac{S_{i,t}}{Q} \qquad \forall\ i \in \Omega_S,\ \forall\ t \in \mathrm{T} \tag{10}$$

Furthermore, ESS constraints are related to the practical limitations of its utilization. Generally, the impossibility of long time period's operation, no rapid and deep discharge regime, and the predetermined range of ESS state of charge are the common practical constraints of energy storage systems [34]. The storage units' power and energy constraints can be modeled as follows:

$$|P_{ESS_{i,t}}| \leqslant P_{ESS_i}^{\max} \qquad \forall\ i \in \Omega_S,\ \forall\ t \in \mathrm{T} \tag{11}$$

$$SOC_{ESS_i}^{\min} \leqslant SOC_{ESS_{i,t}} \leqslant SOC_{ESS_i}^{\max} \qquad \forall\ i \in \Omega_S,\ \forall\ t \in \mathrm{T} \tag{12}$$

Eq. (11) represents the active charge/discharge power limits of the ESS which must not exceed its maximum range. Furthermore, the ESS state of charge appears as an inequality constraint in Eq. (12). This is a very important issue in ESS operation procedure during the operation time span, which guarantees its maximum lifecycle.

2.3. Problem formulation

Social welfare maximization is the main objective of the proposed MPC control approach for online coordination of DR and ESS facilities considering wind power generation variation. Therefore, the control variables are optimally tuned so as to optimize objective function considering the related uncertainties/constraints. This section includes the objective function and related constraints.

2.3.1. Objective function

As mentioned, the main target of this study is to maximize the social welfare of a wind integrated power system. In addition, minimizing the cost of performing DR programs as a side objective is considered in the objective function. The corresponding objective function is presented in Eq. (13).

$$Objective\_function = Minimize\left(\sum_{t=1}^{T}\sum_{i=1}^{N_b} \left(\frown(C_i(P_{G_{i,t}}))^A + \frown(P_{DLCDR_{i,t}} C_{DLCDR} + \delta_{i,t} P_{LSDR_{i,t}} \times C_{LSDR})^B\right)\right) \tag{13}$$

As seen the objective function is comprised of two different parts. These parts imply the social welfare maximization as part A and minimizing the imposed cost of DR programs as Part B.

Social welfare refers to the sum of net consumers' surplus and producers' profit. In other words, social welfare can be calculated considering the difference between consumers' benefits $B(P)$ and the cost of generating the related energy $C(P)$.

$$Max\left(\sum B(P) - C(P)\right) \tag{14}$$

As a matter of fact, market operators should determine market clearing price by receiving customer's offers as well as the power producer's bids in a pool-based electricity market. So, selection of the accepted bids and offers determines the market clearing price. This process should take place in a way to maximize economic welfare considering all security constraints. Therefore, the optimal dispatch scheduling of the customers and the power producers is the common solution for maximizing social welfare in a pool based electricity market. It is noteworthy to point that, according to [35], the demands are anticipated to be insensitive to price. In fact, the corresponding benefit of the consumers is constant and it is not needed to be taken into consideration in the optimization. In addition, due to lack of a certain equation or at least a very complicated one for customer's offers, the only parameter to be scheduled is the power producer's bids [36]. So, the equation above will change in the following manner:

$$Social\ \ Welfare = Maximize\left(\sum_{i=1}^{N_b} -C_i(P_{G_i})\right) \tag{15}$$

where

$$C_i(P_{G_i}) = a_i {P_{G_i}}^2 + b_i P_{G_i} + c_i \tag{16}$$

Obviously, the maximization function converts to a minimization one due to the negative sign in the above equation.

$$Social\ \ Welfare = Minimize\left(\sum_{i=1}^{N_b} C_i(P_{G_i})\right) \tag{17}$$

In fact, minimizing the cost of power production in a pool-based electricity market can consequently increase social welfare.

On the other hand, economic evaluation of energy trading in a pool based electricity market with constrained transmission lines requires the use of locational marginal prices (LMPs). Calculation of these prices is achieved using an optimization procedure, which maximizes social welfare [35].

LMPs are the Lagrange multipliers or shadow prices of the optimal power flow (OPF) problem addressed in Eq. (17) considering network constraints. Linearized DCOPF problems are commonly used to approximate the nonlinear AC optimal power flow problems in power market with following assumptions [37]

(1) The resistance of each branch can be neglected compared to its reactance
(2) Voltage magnitude of each bus is equal to the base voltage almost one per unit.
(3) The corresponding difference between the voltage angles of the adjacent nodes over a branch is small enough to assume $\cos(\delta_n - \delta_m) \approx 1$ and $\sin(\delta_n - \delta_m) \approx (\delta_n - \delta_m)$.

In this respect, DCOPF is a way to optimize Eq. (17) taking into account constraints (18) and (19) [38].

$$\sum_{i=1}^{N_b} y_{nm}(\theta_n - \theta_m) = P_i \qquad \forall\ i \in \Omega_b \tag{18}$$

$$y_{nm}(\theta_n - \theta_m) \leqslant F_{nm}^{\max} \qquad \forall\ (n, m) \in \Omega_l \tag{19}$$

where Eq. (18) assures the power balance in each network bus and Eq. (19) restricts the power flow of each transmission line to its maximum

thermal limit. The Lagrange function of the optimization problem is defined as Eq. (20).

$$l = \sum_{i=1}^{N_b} C_i(P_{G_i}) + \sum_{i=1}^{N_b} \pi_i \left[P_i - \left(\sum_{j \in \Omega_L^i} y_{nm}(\theta_n - \theta_m) \right) \right] + \sum_{n=1}^{N_b} \sum_{m=1}^{N_b} \tau_{nm} [F_{nm}^{\max} - y_{nm}(\theta_n - \theta_m)] \tag{20}$$

Using the Lagrange multipliers of the assumed DCOPF model, the LMP at each bus is obtained as Eq. (21) [3]. Where the calculated price is sum of the slack bus and congestion prices, while, power loss cost is neglected based on DC power flow [39–43].

$$LMP_{i,t} = LMP_{i,t}^{energy} + LMP_{i,t}^{congestion} = \pi_{i,t} + \sum_{(n,m) \in \Omega_L} GSF_{nm,i} \times \tau_{nm,t} \tag{21}$$

In this equation, GSF is the generation shift factor which determines the percent of the power flow variation in the line nm, if the net injected power at the bus i changes by one MW.

2.3.2. Network constraints

Network constraints are related to some of the constraints which guaranty the feasibility of a generation schedule based on network configuration and generation units limits. As a matter of fact, network constraints refer to the technical constraints that directly affect the operation procedure. Indeed, in power system optimization there are two major equality and inequality constraints of the optimal power flow problem. The equality constraints are a kind of non-violating constraints which must satisfy an equality equation. In fact, equality constraints refer to the power system model [44]. Eq. (22) ensures the load and generation balance. In other words, the power generation of conventional units, wind generators, and the charge/discharge regime of the ESS must match the required energy considering DR programs. Besides, there are several practical operational constraints as the inequality constraints. It's noteworthy to point that, the inequality constraints must satisfy inequality equations within a pre-determined range as stated in Eqs. (23)–(25). Eqs. (23) and (24) are the conventional and wind generators power limits and Eq. (25) presents the power flow thermal limit of the transmission lines.

$$\sum_{i \in \Omega_G} P_{G_{i,t}} + \sum_{i \in \Omega_W} P_{W_{i,t}} + \sum_{i \in \Omega_S} P_{ESS_{i,t}} = \sum_{i \in \Omega_D} P_{D_{i,t}} + \sum_{i \in \Omega_{DR}} P_{DR_{i,t}} \quad \forall\, t \in T \tag{22}$$

$$P_{G_i}^{\min} \leqslant P_{G_{i,t}} \leqslant P_{G_i}^{\max} \quad \forall\, i \in \Omega_G, \forall\, t \in T \tag{23}$$

$$0 \leqslant P_{W_{i,t}} \leqslant P_{W_i}^{\max} \quad \forall\, i \in \Omega_W, \forall\, t \in T \tag{24}$$

$$f_{nm,t} \leqslant F_{nm}^{\max} \quad \forall\, (n, m) \in \Omega_l, \forall\, t \in T \tag{25}$$

As a result, Eq. (13) reflects the objection function of the optimization problem to be solved so as to optimally determine $P_{G_{i,t}}$, $P_{W_{i,t}}$, $P_{ESS_{i,t}}$, $\delta_{i,t}$ and $P_{DLCDR_{i,t}}$ to coordinate the ESS operation plan and DR programs in company with satisfying all of network, ESS and customers' requirements/constraints.

2.4. Proposed MPC approach

In this section, first, the proposed MPC approach methodology is described and then its capability to cover the regarding wind generation and customer's behavior uncertainties is discussed.

2.4.1. Methodology

Considering a great deal of uncertainties concerning wind power generation and amount of energy to be satisfied at a specified duration of time in LSDR program, it is rational to create an adaptive and updatable prediction model, as a feedback signal, to provide a possibility for the measurement or estimation of future system condition. Besides, being real-time is a special feature which can mitigate the negative impacts of substantial uncertainties in practical implementation. Hence, it is also important to develop a system to work in a discrete-time manner. The key advantage of MPC method is that by considering

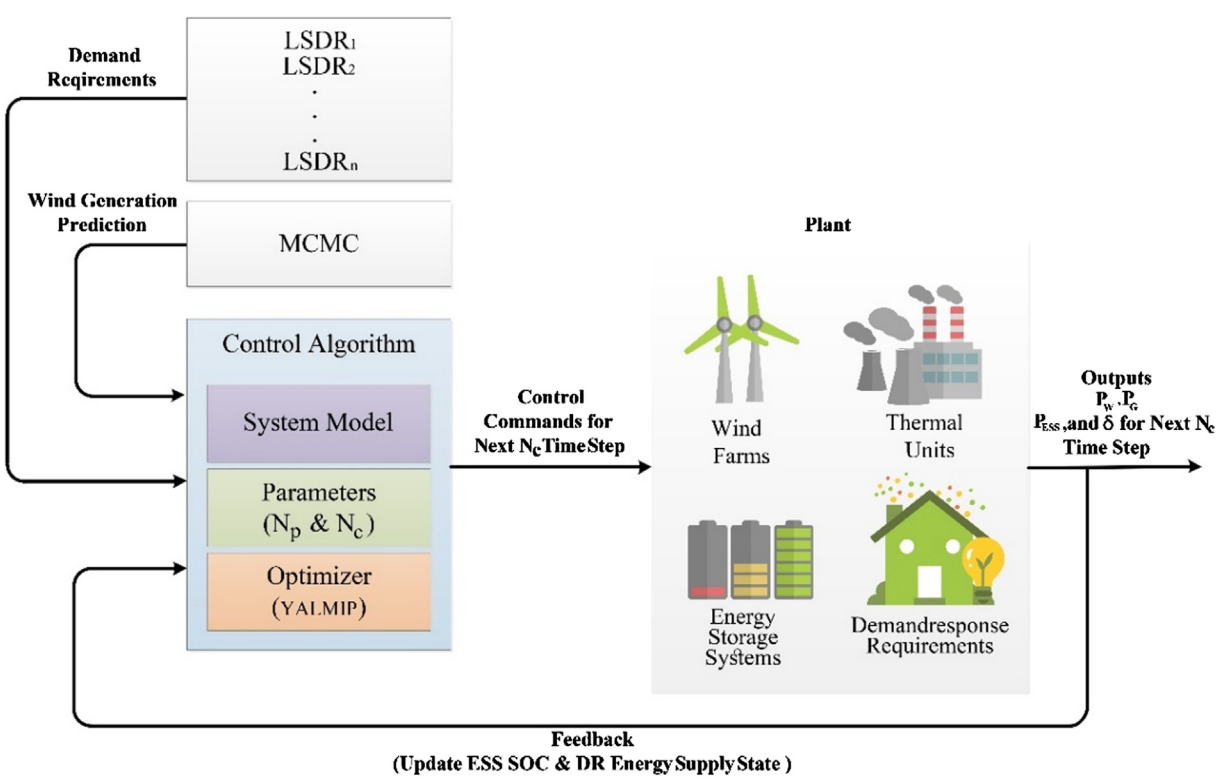

Fig. 2. The conceptual framework of the control process.

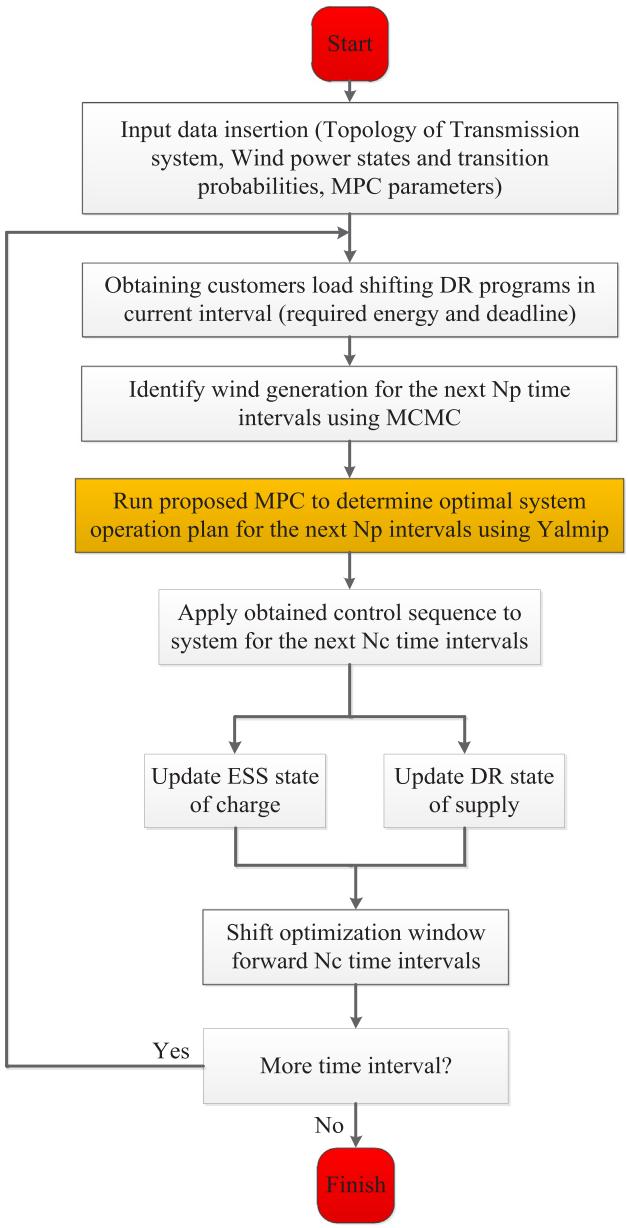

Fig. 3. The hierarchical structure of the proposed method.

future time intervals, allows the current time interval to be optimized, simultaneously. Taking all these considerations into account, designing of an MPC-based approach is particularly suited to handle the aforementioned challenges. In brief, discrete time manner, re-optimization characteristic, and adaptability make MPC technically well-suited for the purposes of the present study. As a whole, MPC design goal is the calculation of future direction to optimize the future of the plant. In fact, optimization would be conducted within limited time window accounting plant information at the beginning of time window. It is worth mentioning that the basic concepts of MPC are detailed in [45] and [46]. In addition, the introduction and implementation of MPC in MATLAB environment are provided in [47].

The plant under control in this study is comprised of a power system in transmission level including conventional thermal generation units, wind generation units and energy storage systems as well as responsive loads. The goal of the control algorithm is power system operation optimization by minimizing Eq. (13), while, taking into account the DR, and ESS models and network constraints, subject to periodic updates concurrently with the operation.

With this background, three key elements are required to design an efficient MPC-based algorithm: model, MPC parameters (N_p, N_c) and the optimizer.

Model is the most important part of an MPC algorithm. The model is used by MPC to predict system behavior after applying a sequence of control commands and so determining what control sequence will bring system to the target in the future. The system model should be specific and accurate, otherwise, it should be estimated that it introduces approximations to the problem. In this paper, the model includes the objective function, DR, and ESS models and the network constraints.

MPC control approach has two main parameters which should be properly adjusted. The first one is the prediction horizon (N_p), which determines the number of future time intervals that MPC involve them in decision-making process. In other words, only the next N_p intervals are considered by MPC to find the optimal sequence of control commands in each time step. The proper value for N_p depends on the system characteristics and how the input parameters change in the future. However with increasing N_p optimization variables and consequently the optimization complexity and time increase. The second important parameter of MPC is control horizon (N_c), which determines the number of control command sequences which will be applied to the system after each time the optimization runs. In other words, MPC will determine the optimal control command sequences for the next N_p time intervals in each time step, but only N_c of them will be applied to the system ($N_c \leqslant N_p$). Then optimization window goes forward N_c time steps and the optimization is done again using the updated input data. It should be noted that an increase in N_c, decrease the number of optimization running and so optimization time but may decrease the optimality of results.

The optimizer is the other main part of the MPC control strategy since it provides control activities. In fact, the ability of online optimization requires an efficient technique which solves the problem as fast as is possible. For this purpose, YALMIP as a powerful optimization toolbox of MATAB has been selected in this paper. YALMIP provides a fast optimization tool in MATLAB and stands for yet another linear matrix inequality parser. YALMIP is able to solve the convex and non-convex problems through its modeling language with MATLAB syntaxes. In this optimization toolbox, the user defines the problem in a high-level model and YALMIP itself categories the problem. Thereafter, the most suitable solver is selected to convert and solve the problem in a low-level model [48]. Fig. 2 illustrates the conceptual model of the proposed control approach.

As can be seen in Fig. 2 the inputs of the control algorithm are as follows:

1- Predicted power of wind generation units in next N_p intervals.
2- Amount of energy and supply deadline announced by responsive loads (new requests).
3- ESS State of charge and DR state of supply (previous requests) after performing the control commands in next N_c intervals.

Also, the outputs of the control algorithm are as follows:

1- Optimal power generation of wind power plants in the next N_c intervals.
2- Optimal power generation of conventional thermal power plants in next N_c intervals.
3- Optimal charge/discharge plan of ESS in next N_c intervals.
4- Optimal LS and DLC programs in next N_c intervals

The overall flowchart of proposed MPC developed in this work is presented in Fig. 3, in which whole stages are executed at a given time interval in a stepwise manner.

First of all initial data such as the topology of the transmission system, wind power states, and transition probabilities, as well as MPC parameters, have been received. After inserting the initial data, the

periodic process of algorithm executes the following steps:

1. *In current time step the information's of customers about their LS demand response program is received; in other words, (i.e. the amount of energy and supply deadline of each load bus of the system).*
2. *Predict wind generation for the next N_p time intervals using MCMC.*
3. *In this step, the MPC determines the optimal control sequence for the next N_p time intervals using system model and YALMIP optimizer.*
4. *In this step, only N_c out of N_p control sequences are applied to the system and the ESS state of charge and DR state of supply will be updated.*
5. *Finally, the optimization window shift forward N_c time intervals and the process continues by skipping to step 1 provided that more time intervals are remaining.*

It should be noted that in each time interval the optimal control sequence for the next N_c time intervals will send to network elements through communication architecture.

2.4.2. Uncertainty mitigation capability

Considering two major features of being online and predictive, offers an exclusive control strategy in optimal operation of wind integrated power systems regarding the uncertain nature of wind power generation and customer's behavior.

Being online enables the controller to access the updated information in each time interval. To this end, the amount of flexible demand with its corresponding deadline time is received by the operator in each time interval. Afterward, the controller takes the whole related changes into account and the updated load data are considered for the next optimal decision making. Accordingly, this online functionality brings about an updatable load profile data for demand-side management considering the related uncertainties. It's worth mentioning that the online feature of the proposed controller is achieved in case of considering which means that the only first optimal control command is applied to the system in each time optimization runs. Then, the decision-making window shifts forward to the next time interval and the mentioned process continues, repeatedly.

Besides, being predictive is a key feature for optimal real-time management of power system considering wind power variations. Indeed, the optimal decisions of the current time interval are dependent on the future system condition (wind power and load variation, flexible loads request, etc). This issue implies that the proposed controller considers the future available wind power variations in current time interval decision making. To this end, MPC considers the estimated wind power generation of the whole prediction horizon, to determine the optimal control plan of the current time interval. Thus, the optimal coordinated control of ESS and DR facilities in the current time interval is affected by the uncertain variation of the estimated future wind power. In other words, due to the time-dependent function of ESS in current and future time intervals, MPC suggests an optimal coordinated control command for managing wind uncertainty impacts considering the future occurrences. Thus, in each time interval, MPC schedules the ESS charge/discharge regime in accordance with the wind power dispatch considering the forecasted wind power in future time intervals. In fact, optimal control decisions of each distinctive time interval are determined in such a way to maximize the utilized wind power and consequently enhance social welfare in the whole prediction horizon.

Therefore, being online and predictive and especially the re-optimization characteristic of the proposed MPC approach, which makes it possible to use the update information of the current and future system condition, increase the robustness and effectiveness of the proposed control approach.

3. Simulation results and discussion

Toward evaluating the efficiency of MPC, it is implemented on the 8 bus test system presented in Fig. 4 with 11 transmission lines, six conventional thermal generation units, one wind farm, and five load points [49]. The ESS capacity is about 50 MWh, while, its maximum output power rate is 2.5 MWs. Simulation has been conducted for one day (24 h) and each time interval is assumed to be 1 h. It should be noted that the length of each time interval can be smaller in cases where updating the input parameters occurs faster. Simulation has been done on a personal computer with core i3 CPU and 4 GHz RAM.

Fig. 5 depicts the variation of the rigid load during the day. Also, there is shiftable load in each hour that is announced by customers in each load bus along with their supply deadlines. This part of the load is

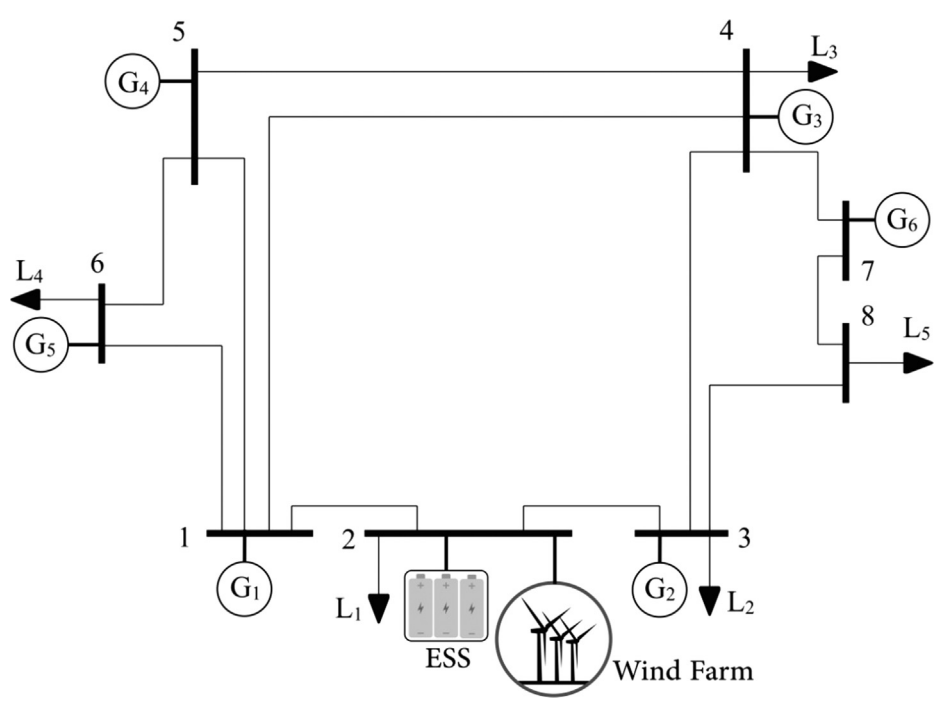

Fig. 4. Eight bus test system.

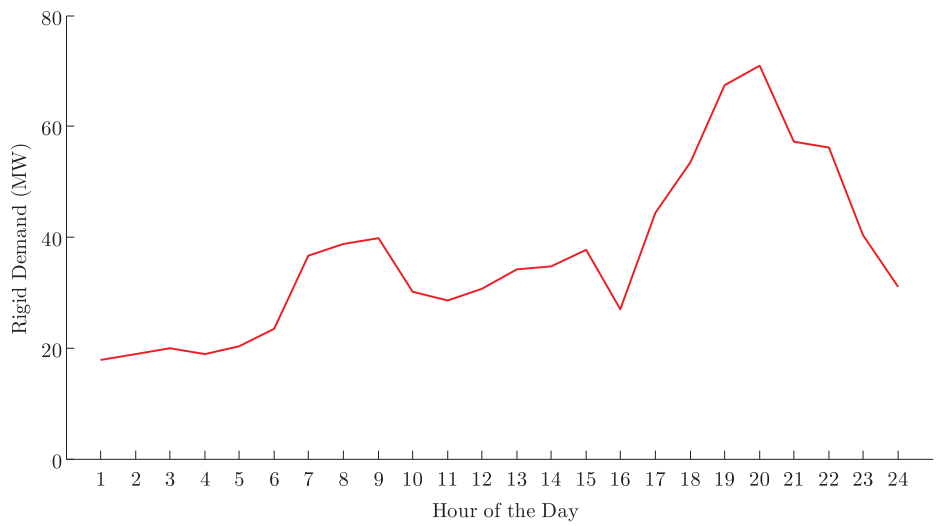

Fig. 5. Rigid load profile during the day.

shown in Fig. 6.

As mentioned, five different states of the Markov chain are considered which cover the most probable wind power generation of the region. Furthermore, the transition probabilities are determined based on the statistical analysis of real wind data. The transition probability matrix is presented in Table 1 [50].

It is seen that the high probability of the main diagonals, prevents sudden changes in wind farm output power. Meanwhile, the initial states for the first state have been generated randomly. Fig. 7 represents the wind power generation during the day based on the MCMC approach. The wind farm output power varies from 14 to 35 MWs, which is the maximum wind capacity in this study. It is worth noting that the wind farm has been considered to be as a negative load which injects free cost power to the network.

In the following, three different scenarios have been studied to show the effectiveness of the proposed control approach as below:

Case A: Online-not predictive control approach
Case B: Predictive-not online control approach
Case C: MPC control approach

More detailed description of each approach will be presented in the related subsections. In addition, the simulation parameters are all listed in Table 2.

Table 1
Transition probabilities of the states.

S_j/S_i	1	2	3	4	5
1	99.01	0.98	0.01	0	0
2	18	73.05	8.68	0.23	0.05
3	0.33	31.19	45.21	20.96	2.31
4	0	2.55	32.29	37.11	28.05
5	0	0	3.28	12.31	84.4

3.1. Online-not predictive control approach (Case A)

In this case, it is assumed that $N_p = N_c = 1$. So, the prediction and the control horizon are equal to their minimum possible values. In fact, the system controller runs an optimization considering only the system situation at that time step. Indeed, $N_p = 1$ implies that the controller just considers the current time interval in its optimal decision making, which means that it is not predictive. In other words, the system controller does not consider future condition and information of the system and use only the current system situation and information for optimal decision making. On the other hand, $N_c = 1$ means that the only first

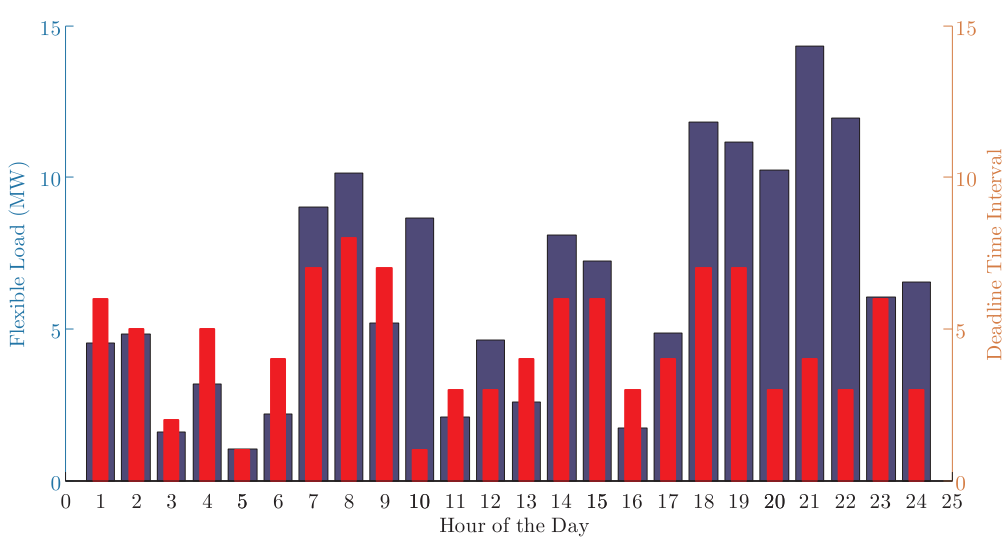

Fig. 6. Responsive loads and their deadline during the day.

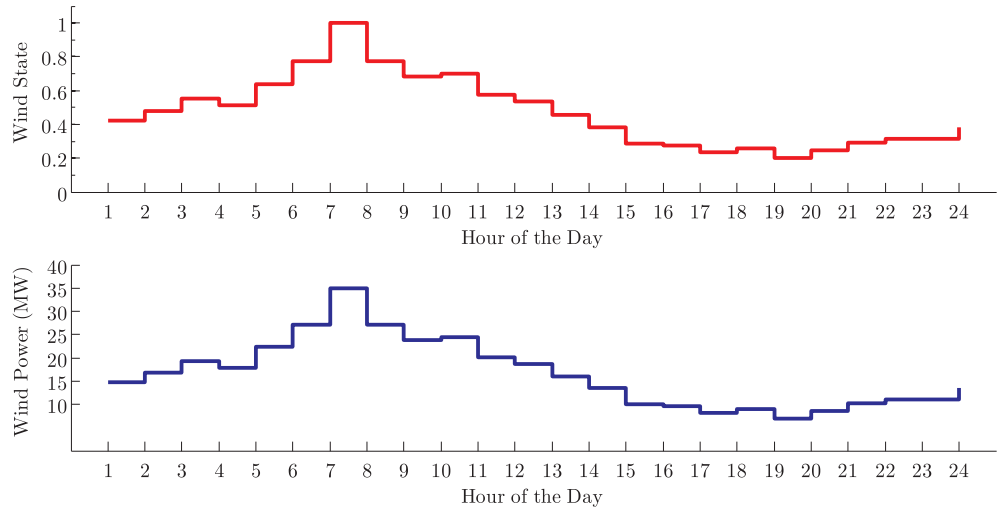

Fig. 7. Wind states and corresponding power during the day.

Table 2
Simulation parameters.

Parameter	Unit	Value
S_{base}	MVA	50
N_p	–	$\overbrace{N_p = 1}^{CaseA}$, $\overbrace{N_p = 24}^{CaseB}$, $\overbrace{N_p = 24}^{CaseC}$
N_c	–	$\overbrace{N_c = 1}^{CaseA}$, $\overbrace{N_c = 24}^{CaseB}$, $\overbrace{N_c = 1}^{CaseC}$
Q	MWh	50
$SOC_{initial}$	–	0.5
SOC_{ESS}^{max}	–	1
SOC_{ESS}^{min}	–	0.1
P_{ESS}^{max}	MW	2.5
η_i^{ch}	–	0.9
η_i^{disch}	–	1
C_{DLCDR}	\$/MWh	45
C_{LSDR}	\$/MWh	0.1

computed control command is applied to the system and then the controller recedes to the next time interval for a new optimization with updated data which assures its online feature. This process continues repeatedly for the whole operation period. So, the controller of case A is not predictive but it is online as it optimizes system variable in each time interval without considering the future system condition.

Fig. 8 shows the optimal charge and discharge plan of ESS as well as its SOC in this control strategy. As can be seen, the ESS discharges with maximum rate in early time steps until the ESS state of charge reaches its minimum limit. After that, no charge or discharge occurred until the end of the operation period, which means that ESS can't help the system effectively through discharging in peak-load hours due to the non-predictive behavior of the control strategy.

Also, as shown in Table 3, the flexible loads supplied immediately after the announcement (see Fig. 6) and the controller has not used the authorized deadlines for cost reduction trough shifting them to off-peak or high wind generation hours. In other words, the controller can't shift loads due to its non-predictable nature ($N_p = 1$) and all flexible loads should be supplied as soon as the declaration (at the corresponding time interval). In fact, the controller in this control strategy tries to optimize system operation in each time step which does not necessarily lead to optimal operation of the system in total operation period. On the other hand, the non-optimal operation of ESS and DR coordination lead to considerable daily load shedding within 35.8429(MWh). Also, based on Table 4, the daily wind generation power is 273.1419(MWh).

3.2. Predictive-not online control approach (Case B)

In this case, both N_p, N_c are the highest possible (considering the daily basis analysis of this study) and are equal to each other $N_p = N_c = 24$. Therefore, the controller is predictive, as it considers the whole 24 future time intervals in the optimization process, considering

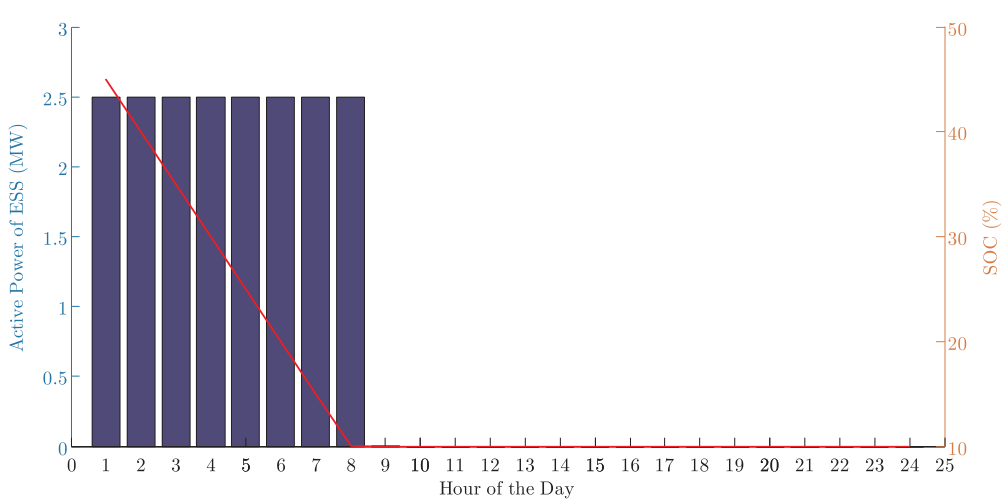

Fig. 8. Charge and discharge plan and SOC of ESS (Case A).

Table 3
Load Management of different scenarios.

Hour (Time)	Flexible Load (MW)			Load Shedding (MW)		
	Case A	Case B	Case C	Case A	Case B	Case C
1	4.5288	2.8704	7.7868	0	0	0
2	4.8379	5.1888	4.5773	0	0	0
3	1.6027	1.9535	1.6564	0	0	0
4	3.1777	3.1777	3.8068	0	0	0
5	1.0335	1.5119	2.7977	0	0	0
6	2.1933	2.6717	6.1182	0	0	0
7	9.026	9.026	3.8138	0	0	0
8	10.1303	10.1303	4.2804	0	0	0
9	5.1771	5.1771	2.5886	0	0	0
10	8.6513	8.6513	10.4896	0	0	0
11	2.0898	2.0898	2.9397	0	0	0
12	4.6385	4.6385	4.8648	0	0	0
13	2.5805	2.5805	2.866	0	0	0
14	8.0923	8.0923	4.309	0	0	0
15	7.2235	7.2235	11.1229	0	0	0
16	1.7188	1.7188	8.4026	0	0	0
17	4.8765	4.8765	6.9817	0	0	0
18	11.8250	11.8250	4.0436	5.3684	2.8684	0
19	11.1659	11.1659	2.359	10.6463	8.1463	5.7873
20	10.2315	10.2315	2.1616	9.6169	7.1169	4.9553
21	14.3136	14.3136	4.6944	5.8485	3.3485	0
22	11.9471	11.9471	8.9236	4.3628	1.8628	0
23	6.0642	6.0642	15.5727	0	0	0
24	6.5278	6.5278	26.4963	0	0	0.6641
Total Load	153.6535	153.6535	153.6535	35.8429	23.3429	11.4076

$N_p = 24$, and is not online, due to applying the whole control commands in the first time optimization runs, considering $N_c = 24$. It is noteworthy to pay pirticular attention to the point that, although the future situation and information of the system are considered, the dynamic and updated information of the system condition is unavailable for the optimal daily decision-making plans. In fact, the optimizer evaluates the system situation of the whole day considering the available information at the first time interval. Therefore, the only one conducted optimization at the beginning of the operation period determines the optimal operation plan of the whole day. In other words, in this control approach, the optimization is performed only once at the first time interval and the controller does not use the online and updated information.

Fig. 9 depicts the optimal ESS operation plan and its corresponding SOC. As can be seen, ESS is planned in a 24-hour framework to provide the maximum cost saving for the system through discharging in peak-load hours.

It's noteworthy to point that the off-line feature of the controller restricts the accessibility of the system information to only the first time step. Thereby, the only possible situation for load shifting can take place in the first time interval. In fact, the offline controller of this case ($N_c = 24$), optimize the whole day control plan in the first time interval and therefore can just manage the flexible load of the first time step (because there is no information about the amount and deadline of flexible loads in future time intervals). Consequently, all flexible load (except that declared in the first time interval) should be supplied as soon as the declaration (at the corresponding time interval).

Table 3, shows the load management strategy in this case. It is seen that the flexible load of the first time interval is managed to be supplied in the next six hours considering its supply deadline (see Fig. 6). Furthermore, due to the more efficient control of ESS, the amount of load shedding has been reduced to 23.3429(MWh). As a matter of fact, the ESS operation has been managed more effectively compared to Case A. Therefore, the free cost wind power utilization increases and consequently, decrease operation cost (see Table 4). In summary, the predictability of the controller manages the ESS operation for the whole day, considering the available wind power and load variation.

3.3. Proposed MPC control approach (Case C)

Finally, in this subsection, the corresponding results of the proposed MPC approach are presented. This control approach is online and predictive. This means that not only the future situation and information of the system but also the dynamic and updated information of the system condition are considered in the optimization process. In fact, at each time interval, at first, the optimal control sequences are determined considering the prediction horizon. Next, the controller applies the optimal control commands to the system up to the pre-determined control horizon. Then, the situation is updated according to the latest system condition.

In short, the online optimization of the current time interval is affected by the next prediction horizon time intervals. Therefore, the proposed MPC controller performs in a predictive and online manner.

In this case, the prediction and control horizon is assumed to be 24 and 1, respectively. It means that the predictive controller optimizes the system in the next 24 time intervals, but only the first control command is applied to the system to ensure the online feature of the proposed MPC approach. In other words, in each time interval, the optimal control decisions are determined for the next 24 time steps using the whole available and updated data such as flexible load requests of the current time interval and wind power generation prediction. But, the only first control command is applied to the system and the controller recedes to the next time interval and this process continues reputedly for the whole operation period.

Fig. 10 shows the optimal ESS operation plan using the proposed MPC approach. It is seen that the ESS optimal charge and discharge plan is managed in accordance with the wind power and load variation. To this end, ESS is charged in high available wind power generation and later discharged in lower available wind power and peak-load hours. In fact, the ESS acts as a wind energy shifter.

In addition, the flexible loads are shifted to off-peak load hours considering their supply deadlines and the least possible loads are scheduled to be supplied in peak-load hours. As a matter of fact, the predictive feature of the controller in this case ($N_p = 24$) provides a desirable condition to manage and allow the flexible loads to be supplied in future time intervals. Furthermore, its online feature ($N_c = 1$) makes it possible to take the new flexible loads announcements into account at each time interval optimization.

Table 4
Comparison table of different cases.

	Unit	Case		
		A	B	C
Operation Cost	($)	12,638	11,858	11,107
Wind Power Utilization	(MWh)	273.1419	296.4595	311.1942
Model Size	–	$(1 + 5 + 6 + 1) \times 1$	$(1 + 5 + 6 + 1) \times 24$	$(1 + 5 + 6 + 1) \times 24$
Number of Optimization	–	24	1	24
Total Simulation Time	(s)	23.45	5.97	139.1
Simulation Time per Optimization	(s)	0.97	0.24	5.79

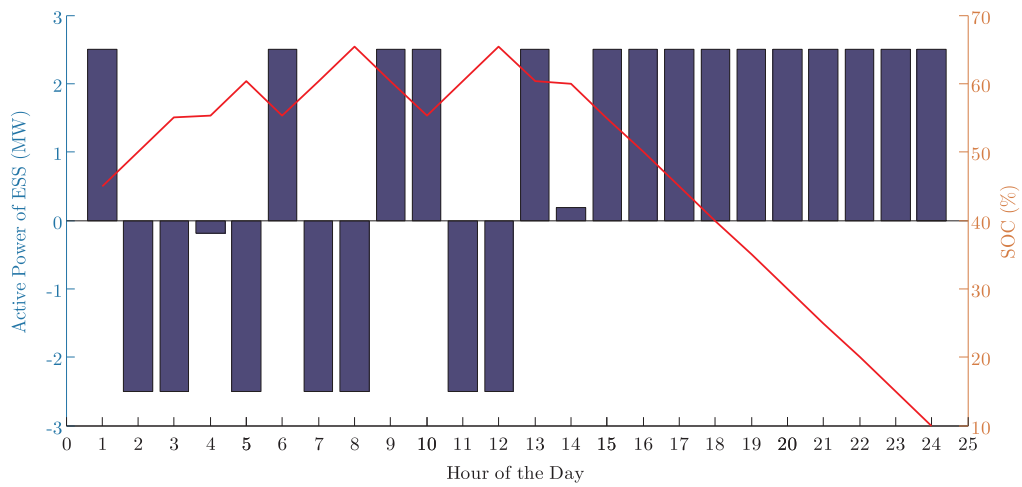

Fig. 9. Charge and discharge plan and SOC of ESS (Case B).

Finally, a comparative analysis between different control strategies based on Table 3, shows the high capability and robustness of the MPC approach in managing both flexible load shifting and load shedding programs.

In Table 3, the total requested flexible load of the customers is equal in all cases during the day. But, it is important to pay particular attention to the manner of flexible load management in different cases. As stated before, the controller in case A can't shift loads due to its non-predictable nature. In addition, the offline controller of case B, optimize the whole day plan in the first time interval and therefore can just manage the flexible load of the first time step. On the contrary, the proposed MPC approach in case C is a robust controller, which can shift and manage flexible loads during the day and reply to the customer's demand considering their deadline time. As an example, it is seen that the MPC controller has the least amount of scheduled flexible loads around the peak-load hours (18:00–22:00) compared to the other controllers. Besides, the amount of the load shedding has decreased to 11.4076(MWh) in case C, which demonstrates the capability of the proposed MPC controller in improving the demand-supply management.

Fig. 11 compares the wind power generation management in different cases. The figure represents the maximum available wind power during the day as well as wind power utilization in three cases. As can be seen, in all three cases, the maximum utilization of wind power generation is not possible due to network constraints. However, the figure confirms that the MPC controller increases wind power utilization to 311.1942(MWh) by congestion management through optimal control of ESS and DR programs (see Table 4).

It's further noteworthy to point that the computational cost is an important aspect regarding the optimal operation of market-based wind integrated power systems using the MPC approach. In fact, considering the frequency of the optimization running beside the necessity of online implementation of the MPC approach, the related computational cost is the main concern to be rational in practical implementations. As a matter of fact, optimal decision making in each time interval should be determined within a reasonable time span to cope with power system operator requirements. Accordingly, we propose the YALMIP optimization toolbox for conducting the optimization process so as to obtain the optimal control commands in an acceptable time span.

Table 4 represents different aspects of three control approaches. As shown in this table, the proposed MPC control approach has the best performance in minimizing daily operation cost. Also, the model size, the number of optimization, and corresponding simulation time are stated in this table.

As can be seen in this table, the model size is proportional to the number of decision variables and the prediction horizon (N_p). In fact, the model size is calculated through multiplication of these two parameters. Moreover, decision variables include one ESS, five load points, six conventional generating units, and one wind farm. The other important factor in the computational cost of different control approaches is the number of optimization runs during the operation period. This factor, which is the function of the control horizon (N_c), is equal to 24, 1

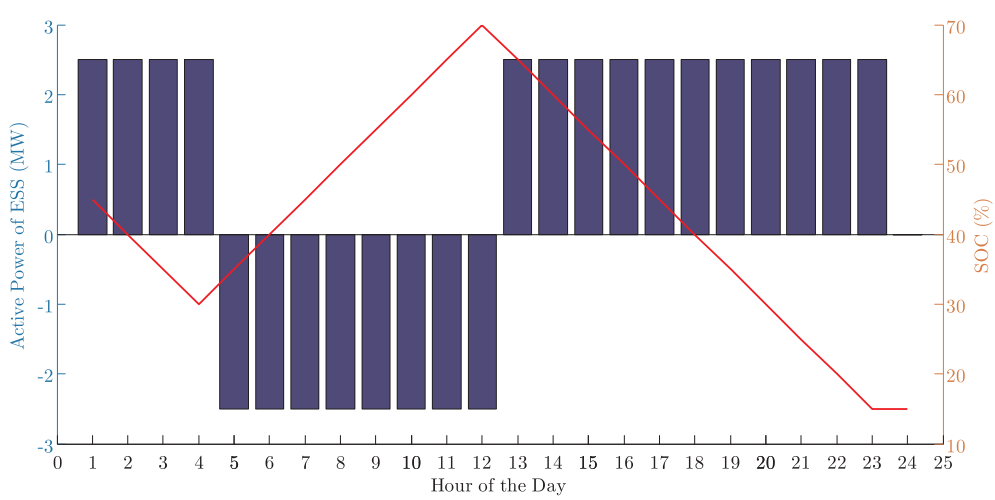

Fig. 10. Charge and discharge plan and SOC of ESS (Case C).

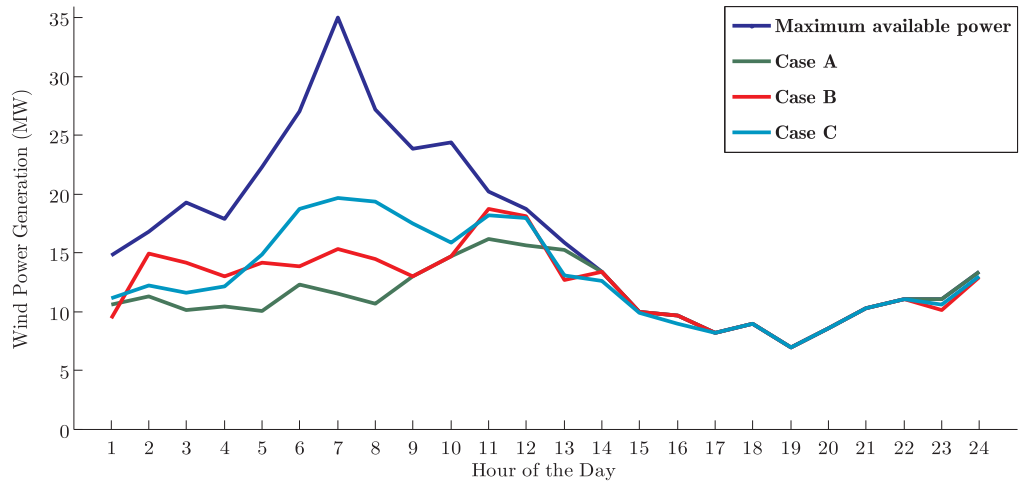

Fig. 11. Wind Power penetration in different cases.

and 24 for the Case A, B, and C, respectively. Thereby, according to the corresponding model size and number of optimization runs, the highest simulation time occurs in case C. It's worth mentioning that, although the model size in case B and C are equal, the only one conducted optimization of case B brings lower corresponding simulation time.

Besides, it is seen that the proposed MPC approach with $N_p = 24$ and $N_c = 1$, makes the system controller to run an optimization in each time step. So, 24 optimization runs in a whole day that takes about 139.1 s (5.79 s for each), which is appropriate and rational for online applications.

Fig. 12 depicts the sensitivity of total daily operation cost and wind generations to prediction horizon in the MPC controller with $N_c = 1$. Although, increasing N_p, increase computational complexity and consequently computational time, but, a considerable decrement in total cost and increment in wind power utilization take place. It's better to mention the point that the prediction horizon is an adjustable parameter which is obvious that greater lead to more optimal solutions. Also, in large-scale power systems, the greater N_p increase in computational time exponentially. So, the appropriate value of N_p should be selected based on the power system scale, so as to be rational in online applications.

4. Conclusion

This paper investigated the optimal operation of market-based wind integrated power systems considering ESS and DR facilities. For this purpose, three control approaches including online but not predictive, offline but predictive and online predictive ones had been evaluated. This paper particularly proposed and focused on the performance of the third control approach named as MPC. The proposed MPC controller coordinates operation of ESS as well as DR programs with the aim of maximizing free cost wind power utilization and consequently social welfare. Also, the uncertain behavior of customers demand considered in the control process and the MCMC approach is hired to model the available uncertain wind power. The objective function is designed to maximize social welfare in an eight bus test system using YALMIP toolbox considering the network, ESS, and DR constraints.

Results demonstrated that the flexibility of the proposed MPC approach brings about 12.18% and 6.3% total daily operation cost saving compare to the first and second control approaches. Also using this approach increased the daily wind energy utilization 13.9% and 4.9% respectively.

In fact, the online and predictive features of MPC helps it to coordinate the ESS operation plan and flexible load supply, in a way that maximizes wind power utilization and social welfare in the operation period. In this respect, the controller manages the ESS charge/discharge

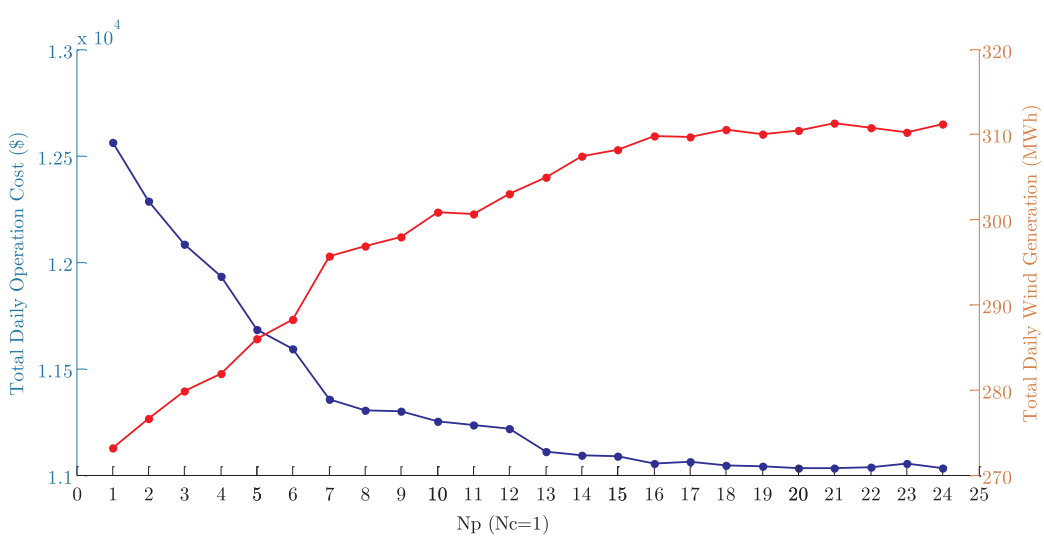

Fig. 12. The sensitivity of the MPC approach to prediction horizon.

regime for the whole day considering the high available wind power and peak loads, effectively. Also, the possibility of load shifting to off-peak hours makes the controller more flexible, which, brings lower amount of the load shedding and improve the supply management. Eventually, according to all of the controlling procedure, wind power utilization increase and improve social welfare. It's worth mentioning that the computational time of proposed MPC is reasonable for practical and online applications.

Future work could, for instance, investigate for the appropriate selection of the prediction and control horizon. In fact, appropriate selection of the prediction and control horizon of the MPC approach depends on the future condition of the system under study. Thereby, the prediction and control horizon must be qualified enough for optimal analysis of different power systems with particular characteristics. In addition, data space management in large-scale power systems is the other suggestion. As a matter of fact, it is essential to manage the required space for data processing in large-scale power systems considering the large volume of data processing and the problem dimensions, especially with great N_p values.

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