INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH
M.Moazzami et al., Vol.8, No.2, June, 2018

Probabilistic SCUC Considering Implication of Compressed Air Energy Storage on Redressing Intermittent Load and Stochastic Wind Generation

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Received: 30.11.2017 Accepted:14.02.2018

Abstract- There are various sources of uncertainty in power systems. Solar and wind forecasting inaccuracies, price forecasting errors, load and demand response forecasting volatilities are some types of uncertainty. In addition, the possibility of outage of power system components such as lines, generating units, and loads can deteriorate the operation condition and compromise the security of power system. Hence, in order to reach a more secure operation, the uncertainties must be included in the scheduling to enhance the robustness and resiliency of power system against possible imbalances and contingencies. The inclusion of probabilistic concepts into the security-constrained unit commitment (SCUC) makes the solution of this problem more complex. However, incorporation of them into the SCUC ensures the secure operation of the power system and inhibits drastic detriments. Furthermore, the compressed air energy storage (CAES) technology is utilized to mitigate the intermittencies and uncertainties. The uncertainties are modeled by using scenario generation techniques. The simulation of a large number of stochastic scenarios considering a variety of uncertainties inclines the results to the most probable condition of realization. The results show that even though the stochastic approaches have higher operational cost but it maintains the security of the system for withstanding against plausible uncertainties and contingencies, which may occur due to whether inaccurate forecasting and consequently inappropriate scheduling or maintaining inadequate generation reserve or transmission capacity. In addition, the integration of CAES units has diminished the total cost of operation and has improved the penetration of renewable resources regard to the congestion of the system, especially at peak hours.

Keywords- Uncertainty; Compressed air energy storage (CAES); Security-constrained unit commitment (SCUC); Stochastic programming; Dispatchability.

Nomenclature:

Indices:

i, c, w	Indices for thermal, CAES and wind units
m, n, z	Bus number
s	Scenario number
t, T	Time interval, total time horizon (24 hours)
c (superscript)	Contingency of *c*

Parameters:

A	The swept area by turbine blades
$A(c,t)$	The level of stored energy in c^{th} CAES at hour *t* (MWh)
a_i, b_i, c_i	Cost functions' coefficients
C_p	The Betz law coefficient
$Cost_{i,t}$	Operational cost
$Cost_i^{Corrective}$	The cost of corrective action after redispatch
D_t, D_t^z	Demand at hour *t*, demand at bus *z*
$E_{c,t}$	The stored energy in the storage *c* at hour *t*
E_c^0, E_c^T	The initial and final value of stored energy in the storage
$I_{i,t}$	Binary variable for state of thermal units
LSF_{mn}^z	The sensitivity of power flow of the line between buses *m* and *n* to power injection at bus *z*
MSR_i	The spinning reserve capacity that can be provided by unit *i* in 1 minute
MUT_i, MDT_i	Minimum up/down time of unit *i*

NL_i	The no-load cost
$OR_{i,t}$, $OR_{c,t}$	The capacity of thermal or storage unit for operating reserve
$P_{c,p}$, $P_{c,s}$	The purchased or sold amount of power by CAES unit
$P_{Dch,c,t}$, $P_{Ch,c,t}$	The consumed / generated electric power by storage in charging/discharging mode
$P_{i,t}$	Active power (MW)
$P^c_{i,t}$,	The generation of unit *i* at hour t after contingencies
$P_{w,t}$, $P_{f,w,t}$	The real and forecasted generated wind power (MW)
P_z	The generated power at bus *z* (MW)
PL_{mn}	The transmitted power from bus *m* to *n*
$\Pr^s$	The probability of occurrence of scenario *s*
QSC_i	The quick startup capacity of unit *i* in 1 minute
RUR_i , RDR_i	Ramp up/down rate of unit *i*
$R_{Spinning,t}$, $R_{Operating,t}$	The spinning and operating reserve required
$SR_{i,t}$, $SR_{c,t}$	The capacity of thermal or storage unit for spinning reserve
$SUC_{i,t}$, $SDC_{i,t}$	The startup/shutdown cost of unit *i* at hour *t*
u^{inj} , u^{exp}	The state of CAES unit
UP_i , DP_i	Shutdown/start-up ramp limits of unit *i*
UT_i , DT_i	The numbers of hours unit *i* must be initially online and offline due to its minimum on/down time restrictions
v_{CO} , v_R , v_{CI}	Cut-out, rated, cut-in speed and wind
$v_{w,t}$	The wind speed of wind farm *w* at hour *t*
V^{inj}	The amount of injected air into the salt cavern by *c*-th CAES (MW/h)
V^{exp}	The amount of pumping air into the combustion chamber by c^{th} CAES (MW/h)
$X_{i0}{}^{on}$, $X_{i0}{}^{off}$	On/off time counter of unit *i* at the initial status
X_{mn} , X_{mi} , X_{ni}	Reactance of line between buses
$y_{i,t}$, $z_{i,t}$	The startup/shutdown indicator
α^{inj}_c , α^{exp}_c	The yield of injected/expanded power to/from c^{th} CAES
δ_m , δ_n	The voltage angle at bus *m* and *n*
$\Delta^c_{i,t}$	The redispatch allowable change after contingencies
$\Delta P^s_{i,t}$	The redispatch allowable change after implementation of scenario *s*
η_c	The efficiency of CAES
μ	The mean of normal distribution
ξ	A factor for defining the range for random generation of stochastic parameter
ρ_{air}	Air density
σ	The standard deviation of normal distribution
ψ	The distance from the mean of normal distribution

1. Introduction

There are various researches conducted in the power system operation considering deterministic values and approaches. However, a practical and realistic model of power system requires the consideration of uncertainties and volatilities. There are many sources of uncertainty in a power system such as the possibility of the outage of generating units, loads, and lines, forecasting inaccuracies of price and load, and the forecast error of photovoltaic, wind power, and demand response resources [1]. In order to take these intermittencies into account, different methods such as stochastic-based, probabilistic-based, fuzzy logic-based or chance-constrained approaches are developed [2-5]. Even though such approaches suffer from the high dependency on explicit knowledge of past behavior data of the uncertain parameters, the consideration of uncertainties in the unit commitment (UC) and economic dispatch (ED) problems leads to more accurate solutions, which provides more efficient use of resources and facilitates the decision making under uncertainty. The risk-averse decisions lead the system to pessimistic conditions and deviation from optimum operation. On the contrary, the risk-taking decisions bring the system operational point closer to the proximity of instability margins and detrimental zones [6]. Maintaining sufficient amount of reserve or utilization of any type of large-scale energy storage can help the operator to redress the imbalances caused by uncertainties and reach a better operation schedule. Hence, the schedule must optimize the objective function of the problem and determine the most optimum commitment states of thermal units within a specific interval and also the best form of participation of storage units subject to satisfy all operational constraints. Furthermore, the environmental constraints restrict the optimization problem too, and the constraints pertaining to electricity market enhances the competitiveness between units, which affects the schedule. Moreover, inaccuracy and uncertainty enhance the complexity of scheduling. Although the solution method of such problem considering all deterministic and probabilistic constraints are too much sophisticated, consideration of comprehensive models for UC and ED problems procures considerable economic benefits and have positive impacts on the environmental condition [7]. In addition, although the forecasting errors and the outage of components are inevitable, providing higher levels of reliability for consumers as well as providing a more economical price for electricity and more exploitation of renewable resources imply that uncertainties must be involved in procedure of planning, operation and maintenance schedule to obtain a more secure solution [8]. In the restructured environment, the uncertainty in price forecasting, which is a fundamental factor for price-based unit commitment and bidding strategy of market participants also exacerbate the difficulty of the problem [9]. The utilization of storage units helps to alleviate the market condition by decreasing locational marginal price, mitigation of required amount of fossil-based reserve, inhibition of congestion at peak hours, and reduction of ancillary services required. In this respect, the concept of compressed air energy storage (CAES) technology, which is a novel and emerging storage technology, is deployed to provide the needed storage capacity in the generation scheduling simulation, and the impact of integration of this storage is investigated [10]. Regard to the specific geological requirement of pumped storage units, the CAES can be a suitable alternative, especially for the flat places. In addition, many kinds of research have been conducted in order to improve the efficiency of CAES. Currently, the pumped storage units typically have the efficiency of %65-%80 whereas the best CAES design can reach to the efficiency of 70% in practice [11]. Besides, this technology has yet higher investment cost in comparison with pumped storage technology. However, the ongoing studies predict a brilliant and promising future for CAES technology. The determination of size, quantity, and location of the storage unit(s) are beyond the scope of this study. In order to redress the imbalances caused by various sources of uncertainty and to be protected against consequences of the intermittent behavior of wind resources, the collaborative operation of wind farms and energy storage units is recommended. An electrical storage unit buys the cheaper electricity in off-peak hours and sells it back with a higher price at peak hours. In addition, it can buy the excess generated power of wind units, which must be otherwise curtailed. The wind units can also earn more benefits by performing a cooperative operation with energy storage systems. The storage units can be installed in the location of the wind farm at the same bus or be located in a separate bus and making only financial transactions [12]. The former is not usually possible geologically, and the latter may have some transmission restrictions.

A comprehensive study is conducted on different electrical energy storage technologies, and the integrated operation of them with renewable resources is investigated in [13]. A thorough investigation on generation scheduling of generating units in restructured environment with consideration of environmental aspects and physical operating restrictions such as valve-point loading effect, ramp rate capabilities of units, and prohibited operating zones is addressed in [14]. The impact of sub-hourly unit commitment method on in presence of intermittent power providers is investigated in [15]. Some methodologies for incorporation of uncertainties in operational schedule are provided in [16-18]. In [19], a stochastic survey is conducted to investigate the effect of uncertainty in the unit commitment problem using neural network-based prediction methods. In addition, in [20], some robust optimization methods are presented to solve the security-constrained unit commitment (SCUC) problem, in which the uncertainty concepts are included. The authors of [21] have proposed a chance-constrained method for incorporation of uncertainties into SCUC. In [22], a comprehensive study on probabilistic and stochastic SCUC is provided, in which three SCUC model of stochastic programming (SP-SCUC), Chance-constrained optimization SCUC (CCO-SCUC), and robust optimization SCUC (RO-SCUC) are described and a comparison between these approaches are performed. Moreover, in [23], a scenario-based security-constrained approach is used to obtain a hydro-thermal schedule. In [24], a risk-constrained reliability-oriented method is presented which describes a unit commitment schedule for clearing short-term electricity market with consideration of uncertainties. The authors of [25] have proposed an SCUC model with consideration of reserve and risk concepts to increase the penetration of wind resources. A similar work is conducted in [26] to evaluate stochastic SCUC versus normal UC. Another study has been conducted to model SCUC problem by use of clustering-based approaches. Some studies such as [27] suggest artificial neural network models for dealing with uncertainties to solve SCUC problem [28]. Some authors have also employed heuristic algorithms to solve SCUC while considering wind uncertainties [29].

In this paper, a stochastic-oriented SCUC problem based on modeling of intermittency of wind and loads (sources of uncertainty) is proposed. Besides, the CAES energy storage is utilized to deal with uncertainties. The uncertainties are modeled by employing appropriate probabilistic distribution functions. Then a comparison is carried out between deterministic and stochastic approaches, and the implication of presence of storage units in operational cost reduction and uncertainty mitigation is investigated. The priority of probabilistic SCUC over deterministic SCUC in increasing the penetration of renewable resources, regard to congestion condition of the grid, is also investigated. In addition, the role of storage unit in mitigation of uncertainties is explored. The linear sensitivity factor is also introduced and employed to deal with active power flow restrictions.

The following parts of the study are categorized into four sections. In section 2, a concise explanation of different types of generating units, which are utilized in this study, is provided. This section provides basic concepts and procedure description of thermal, wind and compressed air energy storage units. In section 3 and 4, the security-constrained unit commitment model and the solution methodology are explained respectively. In section 5, the numerical study and the discussion about the results are presented. Ultimately, in the last section, the conclusions are drawn.

2. Fundamental Concepts Definitions

The basic concepts of this study are divided into three parts. In the following parts, the operational constraints of each type of generating unit as well as a summarized description of their procedure are explored.

2.1. Thermal unit model

The equations below denote the thermal units' constraints. Equation (1) shows the cost function of unit i at hour t. Equation (2) denotes the active power restrictions, in which the boundaries of active power generation of unit i are defined. In Eqs. (3) and (4), ramp rate limits of the thermal units within an hour is expressed. According to these equations, the amount of increased/decreased power generation at two consecutive hours cannot exceed a certain amount which is called ramp up/down rate. If the unit is going to start up/shut down, the terms of UP_i/DT_i are added to RUR_i/RDR_i to model the startup/shutdown ramp rate capabilities. In addition, if the stat-up/shutdown ramp limits (UP_i/DT_i) of the unit is much higher than normal ramp up/down rate limits (RUR_i/RDR_i), another auxiliary cap defined by P_i^{max} is imposed to verify the stat-up/shutdown ramp limits. By employing the last term of these equations, the equation will be valid in the entire search space of the problem.

In addition, in Eqs. (5) and (6), the minimum up/down time restrictions are imposed, which drastically tighten the mixed integer programming for values larger than 1 hour. The hot/cold startup restrictions of thermal units are neglected [30-33]. Each one of these equation has three parts. The first part dictates that the unit must remain on/off regard to its initial condition, which is defined as the number of hours that the unit has been on/off before the beginning time of the study. As the third part declares, if the remained hours until the end of entire time horizon (*T*) are lower than MUT_i/MDT_i, and if a startup/shutdown has occurred, the unit must remain on/off till the end of time horizon. The second term will model the minimum up/down time constraints in some intervals when they do not belong to first and third terms.

$$Cost_{i,t} = a_i P_{i,t}^2 + b_i P_{i,t} + c_i \quad (1)$$

$$P_i^{\min} I_{i,t} \le P_{i,t} \le P_i^{\max} I_{i,t} \quad (2)$$

$$P_{i,t} - P_{i,(t-1)} \le RUR_i\, I_{i,(t-1)} + UP_i\left[I_{i,t} - I_{i,(t-1)}\right] + P_i^{\max}\left[1 - I_{i,t}\right] \quad (3)$$

$$P_{i,(t-1)} - P_{i,t} \le RDR_i\, I_{i,t} + DP_i\left[I_{i,(t-1)} - I_{i,t}\right] + P_i^{\max}\left[1 - I_{i,(t-1)}\right] \quad (4)$$

$$\begin{cases} \sum_{t=1}^{UT_i}\left(1 - I_{i,t}\right) = 0 & \Big| \; UT_i = \max\left\{0, \min\left[T, \left(MUT_i - X_{i0}^{on}\right)\right] I_{i0}\right\} \\ \sum_{\tau=t}^{t+MUT_i-1} I_{i\tau} \ge MUT_i\left[I_{i,t} - I_{i,(t-1)}\right] & \forall t = MUT_i + 1, \; \ldots \; , T - MUT_i + 1 \\ \sum_{\tau=t}^{T}\left[I_{i\tau} - (I_{i,t} - I_{i,(t-1)})\right] \ge 0 & \forall t = T - MUT_i + 2, \; \ldots \; , T \end{cases} \quad (5)$$

$$\begin{cases} \sum_{t=1}^{DT_i} I_{i,t} = 0 & \Big| \; DT_i = \max\left\{0, \min\left[T, \left(MDT_i - X_{i0}^{off}\right)\right]\left(1 - I_{i0}\right)\right\} \\ \sum_{\tau=t}^{t+MDT_i-1}\left(1 - I_{i\tau}\right) \ge MDT_i\left[I_{i,(t-1)} - I_{i,t}\right], & \forall t = MDT_i + 1, \; \ldots \; , T - MDT_i + 1 \\ \sum_{\tau=t}^{T}\left[\left(1 - I_{i\tau}\right) - \left(I_{i,(t-1)} - I_{i,t}\right)\right] \ge 0 & \forall t = T - MDT_i + 2, \; \ldots \; , T \end{cases} \quad (6)$$

2.2. Wind turbine model

The output power of wind farm relies on the wind speed and can be calculated by Eq. (7). This equation models the most salient characteristics of a turbine such as cut-in speed (V_{CI}), rated speed (V_R), and cut-out speed (V_{CO}).

$$P_{w,t} = \begin{cases} 0 & v_{CO} \le v_{w,t} \;\; or \;\; v_{w,t} < v_{CI} \\ \frac{1}{2} C_p \rho_{air} A V_{w,t}^3 & v_{CI} \le v_{w,t} < v_R \\ P_{w,t}^{rated} = \frac{1}{2} C_p \rho_{air} A V_R^3 & v_R \le v_{w,t} < v_{CO} \end{cases} \quad (7)$$

This equation describes the output power of a wind turbine, which depends on air density, swept area by the blades of turbine and cube of the wind velocity. *Cp* denotes the Betz law coefficient which implies that any type of wind turbines is not capable to capture more than 59.3% of wind kinetic energy. In the case of lack of sufficient wind speed, the wind units are faced with a deficiency in providing pledged power. In restructured power systems, in such a situation, the owners of generation units with the deficiency in the generation are penalized by the system operator and the deficiency must be compensated by more expensive units. Otherwise, the load shedding must be imposed. On the contrary, if the wind farm exceeded from forecasted generation, the extra power would dissipate, which is called curtailment. This matter necessitates the utilization of grid-scale energy storage technologies in power systems. The storage units are able to redress the imbalances due to wind uncertainties [34, 35].

2.3. Compressed air energy storage model

Different storage technologies have different capacities and response speed and can be utilized for various applications in power systems. However, in recent years, large-scale energy storage technologies have attracted more attention. It is because of the undeniable role of energy storage systems in enhancing the dispatchability of the network and redressing the various natural uncertainties of the power system [36]. In addition, the use of energy storage technologies facilitates the more penetration of renewable resources. The pumped storage is the most commonly used type of storage all over the world. However, CAES is an emerging technology, which competes against pumped storage technology [37]. It should be noted that installation of PS units requires a specific geological criterion. Usually, the CAES technology requires underground salt caverns. However, it can be installed using artificial reservoirs (metal tanks) for small or medium-scale applications [38]. In a CAES unit, the electricity is bought from the network to drive a compressor. The compressor increases the pressure of the air and injects it into the reservoir (salt cavern or tank). Then during peak hours, the CAES unit can generate electricity by releasing the compressed air from the cavern and leading it toward a combustion turbine [39]. New technologies of CAES intend to save the produced heat during compression level and reuse it during generation step. The compressed air after compression process has a higher temperature. Contrarily, it is colder after expansion phase [40]. The generated heat during compression phase can be recovered rather than dissipated to improve the efficiency. This heat can be managed in three thermodynamic processes of isothermal, adiabatic or non-adiabatic [41]. The estimated round-trip efficiency of the adiabatic process in practice is about 70% [42]. For an adiabatic process, the perfect heat insulation is required, and the heat can be stored in a fluid such as molten salt (about 600 °C) or hot oil (about 300 °C) as well as in a solid such as stone or concrete [43]. In a non-adiabatic thermodynamic cycle, most of the heat is wasted. Thereby, the air must be reheated before entering into the turbine, which degrades the efficiency. The isothermal process is not effective for large-scale applications because it requires massive heat exchangers. The first CAES power plant was a 290 MW power plant constructed in Huntorf, Germany. The next project was a non-adiabatic 226 MW power plant in Alabama, USA. The installations of other CAES power plants are under investigation throughout the world [44]. This technology will definitely have a bright future in term of efficiency. Fig. 1 illustrates the paradigm of a CAES cycle.

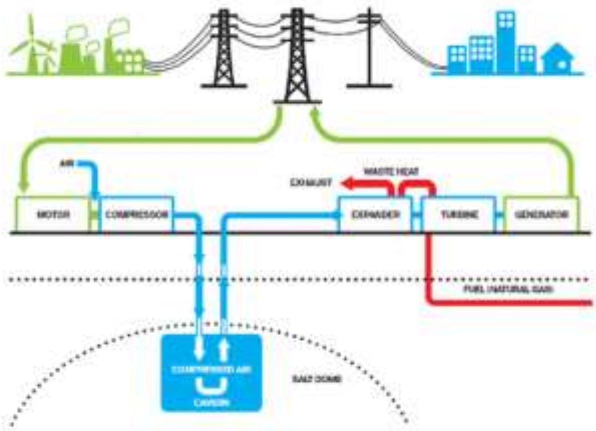

Fig. 1. The structure of compressed air energy storage [45].

The operational constraints of CAES units are expressed as follows:

$$V^{inj}(c,t)=\alpha_c^{inj}P_{c,p}(c,t) \tag{8}$$

$$P_{c,s}(c,t)=\alpha_c^{exp}V^{exp}(c,t) \tag{9}$$

$$V_{min}^{inj}(c)u^{inj}(c,t)\le V^{inj}(c,t)\le V_{max}^{inj}(c)u^{inj}(c,t) \tag{10}$$

$$V_{min}^{exp}(c)u^{exp}(c,t)\le V^{exp}(c,t)\le V_{max}^{exp}(c)u^{exp}(c,t) \tag{11}$$

$$u^{exp}(c,t)+u^{inj}(c,t)\le 1 \tag{12}$$

$$A(c,t+1)=A(c,t)+V^{inj}(c,t)-V^{exp}(c,t) \tag{13}$$

$$A^{min}(c)\le A(c,t)\le A^{max}(c) \tag{14}$$

Equation (8) indicates that how much air is injected into the artificial reservoir or natural cavern. In addition, Eq. (9) represents the active output power of CAES corresponded with the amount of expanded air from cavern into the gas turbine. Equations (10) and (11) impose restrictions on the amount of expanded or injected air. CAES process is made up of two operational modes. The first mode is charging mode (compression of the air and injection into the cavern to be stored). The second mode is known as discharging mode, in which the compressed air is expanded toward combustion chambers of gas turbine. Equation (12) is imposed to inhibit the CAES unit from being simultaneously in both charging and discharging modes. The amount of stored air in the cavern can be updated at each interval by Eq. (13). Ultimately, in Eq. (14), two restrictions are set on reservoir's capacity [46].

3. SCUC Formulation

In general, there are two types of uncertainties in power systems. The first arises from mathematical sense which indicates a difference between estimated/measured value and real value due to inappropriate calculation or measurement. The second source of uncertainty is due to intermittent nature of some non-deterministic phenomena, including fuel and energy price, generation availability, unplanned outages, transmission capacity, load requirements, and market forces [47].

The independent system operator requires a powerful computational tool in order to maintain a generation schedule, subject to meet all generating constraints and to keep operating within security margins. Hence, the transmission line's characteristics must be involved in the calculation. The objective of SCUC is to minimize the operation cost while the reliability of the system is not compromised. The interpretation of reliability involves two subjects of adequacy and security. The adequacy denotes on providing enough generation resources for satisfying the peak of demand and maintaining sufficient reserve [48]. A secure operation indicates the ability of the system to supply the demand continuously in spite of changes due to uncertainties and contingencies [49]. A simple UC program aims to minimize the operating costs while meeting prevailing constraints such as ramp rates, spinning reserve requirements, load balance, minimum up/down time, hot/cold start up etc. [50]. However, in some cases, the UC cannot find a feasible solution to meet all of the demand due to congestion, or the system cannot withstand volatilities due to contingencies or uncertainties. The SCUC encompasses the network flow constraints and ensures that no transmission line is overloaded even when another line is lost [51].

This study investigates an SCUC model in two scenarios of without incorporation of uncertainties and with consideration of stochastic nature of uncertainties. The uncertainties can be modeled in SCUC using stochastic, robust or chance-constrained optimization approaches. In this study, only the uncertainty of load and wind forecasting are modeled in the SCUC model using stochastic programming.

2.1. Deterministic SCUC

As the base case, the basic model of SCUC is defined by the following equations. As it can be seen in Eq. (15), the objective function of SCUC in the base case encompasses the operation costs, no-load costs, and startup/shutdown costs of thermal units. The load balance condition is illustrated in Eq. (16), where all of thermal, wind and CAES units commit in satisfaction of demand of D_t at hour t. Equations (17) and (18) indicate that the spinning and operating reserves must be provided by thermal and CAES units at each hour. Equation (19) imposes a restriction on generation level of each thermal unit to maintain spinning reserve required. The required spinning and operating reserve capacities can be calculated based on various standards and stochastic or probabilistic approaches. In this study, the spinning reserve required is calculated based on deterministic approach, which is defined as a certain percentage of total loads plus by a certain persentage of forecasted wind generation. Generally, this capacity must be enough large to supply the outage of the largest generating unit. Equation (20) shows the maximum ability of the unit to provide the reserve within 10 minutes when the unit is on. Equation (21) denotes the quick start capability of the unit for providing emergency reserve capacity.

$$\min \sum_i \sum_t \left[Cost_i P_{i,t} + NL_i I_{i,t} + SUC_{i,t} y_{i,t} + SDC_{i,t} z_{i,t} \right] \tag{15}$$

$$\sum_i P_{i,t} + \sum_w P_{w,t} + \sum_c (P_{Dch,c,t} - P_{Ch,c,t}) = D_t \tag{16}$$

$$\sum_i SR_{i,t} + \sum_c SR_{c,t} \ge R_{Spinning,t} \tag{17}$$

$$\sum_i OR_{i,t} + \sum_c OR_{c,t} \ge R_{Operating,t} \tag{18}$$

$$P_{i,t} + SR_{i,t} \le P_i^{\max} I_{i,t} \tag{19}$$

$$SR_{i,t} \le 10MSR_i I_{i,t} \tag{20}$$

$$OR_{i,t} = SR_{i,t} + \left(1 - I_{i,t}\right) QSC_i \tag{21}$$

The uncertain resources must be limited to their forecasted amounts. Hereby, the wind power is restricted by Eq. (22). It should be said that a slight variation in wind speed can be led to a considerable change in output power of wind farms.

$$0 \le P_{w,t} \le P_{f,w,t} \tag{22}$$

The storage model for SCUC problem can be defined by Eqs. (23)-(28). These equations are in a general form for all types of energy storage technologies. Hence, Eqs. (8)-(14) can correspondingly be characterized with parameters of the following equations. For example, the parameter of $E_{c,t}$ have a similar concept of $A(c,t)$ in CAES power plants, upper reservoir volume in pumped storage power plants as well as stored energy in a battery in battery-based storage units. Equation (24) guarantees that the discharging and charging process will not occur simultaneously. Equations (25) to (27) imply the operational ranges of the storage unit. Furthermore, Eq. (28) indicates that the level of energy (stored air in the cavern) at the beginning and the end of the whole period of study (a 24-hour period) must be the same [52, 53].

$$E_{c,t} = E_{c,(t-1)} - \left(P_{Dch,c,t} - \eta_c P_{Ch,c,t}\right) \tag{23}$$

$$I_{Dch,c,t} + I_{Ch,c,t} \le 1 \tag{24}$$

$$I_{Ch,c,t} P_{Ch,c}^{\min} \le P_{Ch,c,t} \le I_{Ch,c,t} P_{Ch,c}^{\max} \tag{25}$$

$$I_{Dch,c,t} P_{Dch,c}^{\min} \le P_{Dch,c,t} \le I_{Dch,c,t} P_{Dch,c}^{\max} \tag{26}$$

$$E_c^{\min} \le E_{c,t} \le E_c^{\max} \tag{27}$$

$$E_c^0 = E_c^T \tag{28}$$

The network power flow restrictions are demonstrated in Eqs. (29) and (30). The linear sensitivity factor method is used to model the DC power flow, where LSF^z_{mn} shows the sensitivity of power flow of the line between buses m and n to power injection at bus z [54].

$$\begin{cases} -PL_{mn}^{\min} \le PL_{mn} \le +PL_{mn}^{\max} \\ PL_{mn} = \dfrac{\delta_m - \delta_n}{X_{mn}} = \dfrac{1}{X_{mn}} \left(\sum\limits_{z=2} X_{mi} P_z - \sum\limits_{z=2} X_{ni} P_z \right) = \sum\limits_z LSF_{mn}^z P_z \\ LSF_{mn}^z = \dfrac{X_{mz} - X_{nz}}{X_{mn}} \end{cases} \tag{29}$$

$$PL_{mn} = \sum_z LSF_{mn}^z \left(\sum_{i \in U(z)} P_{i,t} + \sum_{w \in U(z)} P_{w,t} + \sum_{c \in U(z)} (P_{Dch,c,t} - P_{Ch,c,t}) - D_t^z \right) \tag{30}$$

2.2. Probabilistic SCUC

The deterministic model has difficult solution methodologies. The incorporation of uncertainties into SCUC problem makes the solution more sophisticated. However, if the implication of stochastic phenomena and their subsequent imbalances and volatilities are not evaluated, the schedule is not enough resilient and robust against plausible changes. It is because an appropriate schedule is not provided, and the most optimum units are not called. Besides, sufficient reserve may not be considered, which weaken the system to redress sudden or unplanned imbalances or track the power variation changes. When the intermittency and uncertainty are neglected, this matter may be concluded to higher operational costs, inability to supply the load when an imbalance occurs, unwanted load shedding and generation curtailment, and in rare emergency cases may be led to brown-outs or black-outs. These consequences necessitate the consideration of uncertainties in the system scheduling, especially when a large penetration of uncertain sources and renewable resources are integrated. Hence, the stochastic programming optimization is adopted to model the uncertainties in power system. This approach is based on representing a set of scenarios. The Monte Carlo sampling method can be used to generate random scenarios. To each scenario, a certain probability value is assigned to show its realization possibility. The employment of a large number of scenarios has some disadvantages such as the increase in model size, the expansion of computational burden and being inappropriate for large-scale applications. Hence, scenario reduction techniques such as Latin Hypercube Sampling method can be employed to decrease the scale of stochastic model. Thus, similar scenarios are aggregated and low-probable scenarios are eliminated [22].

In the probabilistic model, all abovementioned equations are valid, and the following equations are defined for contingencies and uncertainties. Equation (31) shows the objective function of stochastic programming SCUC, which has an additional term compared with deterministic objective function. Equation (32) indicates that the change of $\Delta P^s_{i,t}$ in the generation is required to update the schedule of the base case into the scenario s of stochastic programming. The combination of Eqs. (31) and (32) would be resulted in Eq. (33). In Eq. (33), Pr({s}) represents the probability of occurrence of the scenario s, and $P^s_{i,t}$ stands for power generation of unit i at hour t for the scenario of s [55].

$$\begin{aligned} &\min \sum_i \sum_t \left[Cost_i P_{i,t} + NL_i I_{i,t} + SUC_{i,t} y_{i,t} + SDC_{i,t} z_{i,t} \right] \\ &+ \sum_s \Pr{}^s \sum_i \sum_t Cost_i^{Corrective} \Delta P_{i,t}^s \end{aligned} \tag{31}$$

$$P_{i,t}^s = P_{i,t} + \Delta P_{i,t}^s \tag{32}$$

$$\begin{cases} \min \sum\limits_i \sum\limits_t \left[NL_i I_{i,t} + SUC_{i,t} y_{i,t} + SDC_{i,t} z_{i,t} \right] \\ + \sum\limits_s \Pr\left(\{ s : s \in \mathrm{S} \}\right) \sum\limits_i \sum\limits_t Cost_i P_{i,t}^s \\ \mathrm{S} \equiv (s_{wind} \cup s_{load}) \end{cases} \tag{33}$$

In the case of occurrence of a contingency, the generation schedule must be changed properly to keep the system in a secure manner without any congestion in lines in N-1 condition. Hence, as it is shown in Eq. (34), the redispatched power generation of unit i at hour t after the occurrence of a contingency is defined by $P^c_{i,t}$. The parameter $\Delta^c_{i,t}$ denotes the corrective action allowable range, which limits the amount of redispatch for each unit at any time [56,57].

$$\left| P_{i,t}^c - P_{i,t} \right| \le \Delta_{i,t}^c \tag{34}$$

Equations (35) and (36) show the ramp rate restrictions for the transition from the base case to the stochastic scenario of s.

$$P_{i,t}^s - P_{i,t} \le RUR_i^s I_{i,t} \tag{35}$$

$$P_{i,t} - P_{i,t}^s \le RDR_i^s I_{i,t} \tag{36}$$

In this study, the security-constrained unit commitment model is employed while the uncertainty parameters are included. In order to ease the solution of such a model, the DC power flow analysis method is applied.

In order to model various uncertainties of a power system in an optimization problem, some ways are suggested regard to the type of uncertainty. Incorporation of reliability indices such as forced outage rate (*FOR*), mean time to repair (*MTTR*), mean time to failure (*MTTF*) and availability can be modeled for a random outage of units, loads or lines [58]. In addition, the indices of transmission line overload probability (*TLOP*) and loss of load probability (*LOLP*) can be employed for modeling uncertainties by chance-constrained optimization approaches. The employment of probability distribution functions is another type of modulation of uncertainty which is so applicable in stochastic programming approaches. In this study, truncated normal distribution is employed for simulation of the wind and load forecasting error. The normal distribution with notation of $N(\mu,\sigma^2)$ (with a mean value of μ and standard deviation of σ) indicate that occurrences of events are more probable as they are more close to the mean. The forecasting error has approximately similar nature. This fact means that the real value is usually around forecasted value. Hence, the mean of the distribution represents the forecasted wind or forecasted load. According to the normal distribution, 95% of events are probable to occur in the difference of $\pm 1.959964\sigma$ ($\Psi \approx 1.96$) from the mean. Other coverage distances from the mean can be found in the Table 1.

Table 1. The relationship between the distance from the mean and coverage of probable events

$\Psi.\sigma$	Coverage percentage
0.674490σ	50%
1σ	68.2689492%
1.281552σ	80%
1.644854σ	90%
1.959964σ	95%
2σ	95.4499736%
2.575829σ	99%
3σ	99.7300204%

Hence, in order to cover 95% of historical load and wind realizations, the factor of ξ must be defined as below:

$$\xi = \frac{\sigma^2 \psi}{\mu} \tag{37}$$

Therefore, the range of uncertainty of a parameter such as wind speed forecasts or load forecasts must be assigned as $[\mu-\xi.\mu \ , \ \mu+\xi.\mu]$ to cover 95% of all forecasting errors. Therefore, a random number would be generated within abovementioned range so that the possibility of occurrence of the numbers which are closer to the mean is higher than those are far from the mean. Fig. 2 illustrates the bell-shaped curve of normal distribution's probability density function (PDF). Equation (38) defines the value of PDF of the normal distribution [59].

$$\begin{cases} f'(x) = \dfrac{1}{\alpha\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} \\ \alpha = \displaystyle\int_{\mu-\Psi\sigma}^{\mu+\Psi\sigma} \left[\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(t-\mu)^2} \right] dt \\ f(x) = \begin{cases} f'(x) & \mu-\xi\sigma \le x \le \mu+\xi\sigma \\ 0 & \mu-\xi\sigma \ge x \ , \ x \ge \mu+\xi\sigma \end{cases} \end{cases} \tag{38}$$

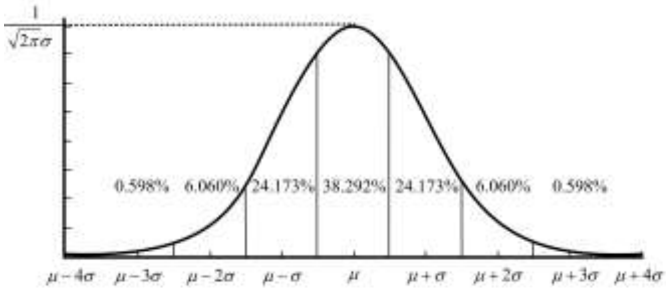

Fig. 2. Normal distribution probability density function curve

As the random variables follow the normal distribution, the possibility of occurrence of each number increases as it is closer to the mean value of distribution. If historical records of an uncertain variable have skewness, the parameter naturally follows the Weibull distribution better than normal. This fact is related to the forecasting method. In a well-done forecasting, the outcomes usually follow the normal distribution.

4. Solution Methodology

The described SCUC problem is mathematically regarded as a large-scale nonlinear mixed-integer optimization problem. This problem contains five binary variables and many continuous and discrete variables as well as series of prevailing equalities and inequalities. Therefore, the SCUC is known as a non-deterministic polynomial-time hard (NP-hard) problem. Various optimization techniques such as Lagrangian relaxation method, mixed-integer non-linear programming (MINLP) and heuristic algorithms have been proposed to attain a near-optimal solution. The procedure of solution is defined in a multilayer program by use of GAMS optimization software. The problem is decomposed in five layers. The master problem calculates the hourly unit commitment schedule, and the second layer determines the economic load dispatch. The third layer evaluates the transmission network restrictions and satisfies the security margins. An iterative process will compute the best units' states and economic load dispatch of units through the loop A between master and two other successive subproblems. When the loop reaches a convergence the base case is calculated. The fourth and fifth layers will model the uncertainties and contingencies. These layers derive the economic dispatch results from the base case and examine the feasibility of scenario. For each uncertain variable, a preassigned number of stochastic scenarios will be generated, and each scenario will be analyzed in the first loop to maintain security margins. Ultimately, the most economic scenario will be shown as the best stochastic solution. The corrective actions and viability of pre-contingency and post-contingency measures will be evaluated through loop B and C, and the appropriate update of the states will be prescribed again in the first and second layer. Fig. 3 depicts the flowchart of solution strategy for SCUC problem.

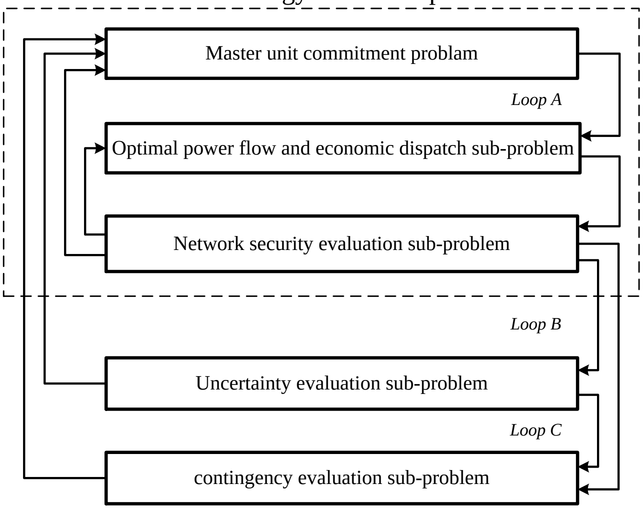

Fig. 3. The diagram of solution approach through master problem and sub-problems

5. Numerical Results and Simulation

In a probabilistic process, the outcomes of events in a large number of experiments will be inclined to the theoretical value. For example, if a person tosses a coin 1000 times, the cumulative probability of being heads or tails will be approximately 0.5. In other words, in a stochastic process with a large number of scenarios, the results will be inclined to the most probable scenario. Hence, when various types of uncertainties are included in the calculation, the most probable scenario will be found considering all interactions of probabilities. Each aggregated scenario (combination of some scenarios) is a possible sample of the solution space. The probability of a specific uncertainty at a specific time can improve or deteriorate the results of another uncertainty. For example, the wind realization is lower than forecasted and the load is higher than predicted. In this case, both probabilities have a negative effect on the objective function. Just the same, the wind is higher and the load is lower than forecasted. In such a circumstance, the objective function will be improved. However, the occurrence of each case is correlated with its probability. Considering a lot of kind of uncertainty (or contingency) for each scenario will result in a more realistic scheduling, which can withstand volatilities and intermittencies and can improve the robustness and resiliency of the operational condition of the system. In another word, the system will have more security in case of incidence of imbalances. Thus, the most probable scenario will be chosen regard to the interaction of all possibilities. The operator can also choose the highest or least probable cases (optimistic or pessimistic forecasting) to decrease the costs or increase the security. In this respect, it can be declared that the risk-taking strategy of the system operator dedicated the level of uncertainty into the scheduling. However, the most probable point is an optimum trade-off between maximum economic benefits and maximum security. In this study, a standard 118-bus IEEE test system is adopted for simulation. All the characteristics corresponded with the test system such as generators' data, transmission lines', and forecasted wind speed data can be found in Table 2 (in appendix at the end of the paper). The characteristics of wind turbines and the CAES units are represented in Tables 3 and 4.

Table 3. The characteristics of wind farms

	Wind farm 1	Wind farm 2	Wind farm 3
Turbines	24	32	36
C_p	0.42	0.45	0.43
ρ_{air}	1.225	1.225	1.225
Blade length	52	52	52
V_{CI}	3	3	3
V_R	20	20	20
V_{CO}	25	25	25
bus	79	118	20

Table 4. The characteristics of CAES unit

	CAES 1
$A^{min}(c)$	400
$A^{max}(c)$	3000
$\{V_{min}^{exp}(c), V_{min}^{inj}(c)\}$	100 (MWh)
$\{V_{max}^{exp}(c), V_{max}^{inj}(c)\}$	500 (MWh)
$\{\alpha_c^{exp}, \alpha_c^{inj}\}$	0.95
bus	49

The SCUC model was comprehensively introduced for various types of uncertainties and contingencies. However, in numerical simulation, only the uncertainty of load and wind power forecasting are modeled. The hourly load is depicted in Fig. 4. The study is carried out in four scenarios as below:

1. Deterministic SCUC without integration of CAES
2. Deterministic SCUC with utilization of CAES
3. Stochastic SCUC without incorporation of CAES
4. Stochastic SCUC with utilization of CAES

In the first scenario, the thermal units are dispatched extensively to meet the demand. The results show that the wind units are not able to inject all extractable wind energy into the grid because of congestion. Some transmission lines are operating at their maximum capability of loading. The overloading of lines has many disadvantages such as aging of overhead lines' conductors and the increase of power losses. It also increases the risk of instability and causes security problems. In addition, it limits the amount of generation in some buses which increases nodal prices in restructured market and enhance the operation cost in traditional systems. In other words, it inhibits the optimal operation of power system. The total installed capacity of wind farms imply that wind farms are able to maximally capture 16084.1 MW of wind energy, if all of the turbines work an entire day at maximum generation level (speculative condition). According to the forecasted wind speeds for the target day, more than 10000 MW of power can be attained by all wind farms. However, all of the wind potential cannot be delivered to the grid. The total extracted wind power in the deterministic approach without utilization of storage unit is about 6710.075 MW.

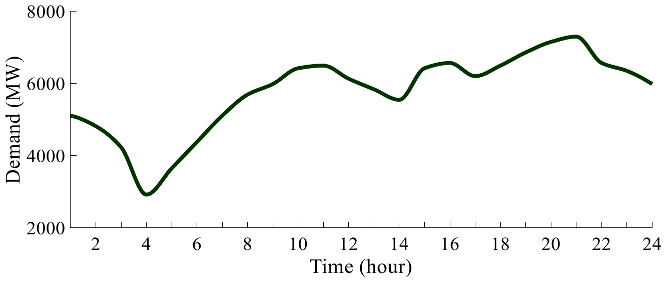

Fig. 4. The forecasted hourly load of test system

Table 5. The forecasted hourly demand data

Time	**1**	**2**	**3**	**4**	**5**	**6**
Demand	5110	4818	4234	2920	3650	4380
Time	**7**	**8**	**9**	**10**	**11**	**12**
Demand	5110	5694	5986	6424	6497	6132
Time	**13**	**14**	**15**	**16**	**17**	**18**
Demand	5840	5548	6424	6570	6205	6497
Time	**19**	**20**	**21**	**22**	**23**	**24**
Demand	6862	7154	7300	6570	6351	5986

In the stochastic SCUC programming, the uncertainties of load and wind forecast are modeled. The SCUC program generates 1000 possible scenarios, in which the possibility of generation of each random value follows the normal distribution. The schedule must be so performed that the system withstands against the most probable scenario among all 1000 generated scenarios. The most probable scenario is found regard to interactions of all uncertainties (and contingencies). According to the load and wind forecast which is obtained based on an extensive database of historical records of demand and wind speed for each wind farm, an independent normal distribution is defined for each hour for any type of uncertainty. For example, for the first hour, N(11.643, 1.33), N(11.863, 1.75) and N(12.482, 2.03) are obtained from the wind data for three wind farms. Hence, the ξ factor can be calculated as 0.223, 0.289 and 0.318 respectively. As it has been introduced, the factor of ξ is calculated so that the normal distribution covers 95% of all possible conditions. Therefore, the random value for the first wind farm will be generated from the range of [11.643-(0.223*11.643), 11.643+(0.223*11.643)]. Such a calculation is assigned for all uncertainties of loads and wind speeds for the entire time horizon.

In the case of incorporation of CAES unit, power generation schedule will change. In this case, the excess wind energy, which had to be dissipated, is stored in the storage unit. The storage unit also absorbs some power from the main grid. Hence, according to Table 7, the operational cost of the system is decreased to $1841987 in comparison with scenario 1 which is $1936540. Furthermore, according to Fig. 5, in scenario 2 (deterministic with CAES), the presence of CAES unit has caused the most penetration of wind units within all scenarios. The first reason is that in the second scenario the most optimistic wind realization is contemplated. The second reason is that the integration of an energy storage unit affects the power flow in the grid in different hours of a day. Fig. 5 shows the total hourly wind power delivered to the grid by all wind farms. Table 7 demonstrates the total generated power by all wind farms at the target day.

Table 6. Total generation cost of each scenario

	scenario	Total generation cost ($)
1	Deterministic without CAES	1936540
2	Deterministic with CAES	1841987
3	Stochastic without CAES	2007979 (± 17675)
4	Stochastic with CAES	1876395 (± 9325)

Table 7. Total generation of wind farms

	scenario	Total extracted wind power (MW)
1	Deterministic without CAES	6710.075
2	Deterministic with CAES	11730.67
3	Stochastic without CAES	2889.73
4	Stochastic with CAES	9827.005

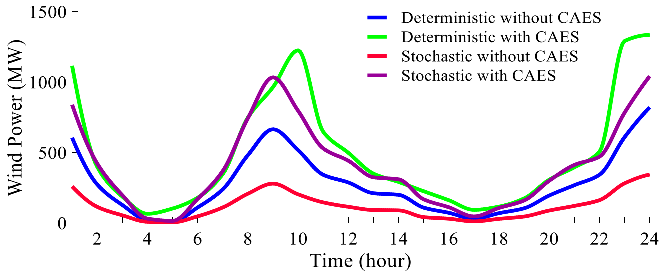

Fig. 5. The overall wind penetration at each hour for all scenarios

The storage usually absorbs power in off-peaks which requires more generation and line capacity. However, the lines' flow conditions are not critical in off-peak hours. In the contrary, the storage unit can generate power in low-congested areas of power system in peak hours which helps to mitigate the congestion in other congested areas of power system. At peak hours, when the system is more likely to have congestion, the storage unit is usually called for generation. The participation of a storage unit (even in a different bus than wind farm) at the peak hours will be led to positive consequences. Some of other power plants must reduce their generation level, and some of them may be obliged to shut down. When new generation level is determined for all generating units, the power flow through transmission lines will change all over the power system. Therefore, the branches connected to the wind unit may have free capacity for transmission. Hereby, the wind farms can inject more wind power to the grid, which had to be curtailed. In addition, the CAES unit has absorbed some of the wind potentials and has prevented them from being wasted. As can be seen in Fig. 6, the CAES unit operates in charging mode in off-peak hours and will be discharged during peak hours which help to decrease the generation cost by preventing commitment of expensive units. Fig. 6 depicts the injection/expansion state of CAES unit. As can be noticed, the unit has the charging state at off-peak hours and the discharging state at peak hours. The CAES unit has consumed 2596.34 MW and has generated 2343.2 MW during a day in the deterministic approach. On the other hand, it has consumed 2430.77 MW in charging mode and has generated 2193.769 MW in discharging mode in stochastic approach. The CAES unit has a similar operation in both deterministic and stochastic approaches to mitigate the imbalances in stochastic approach and increase the dispatchability of wind units in the deterministic method. This matter shows that inclusion of CAES has decreased the impact of uncertainties.

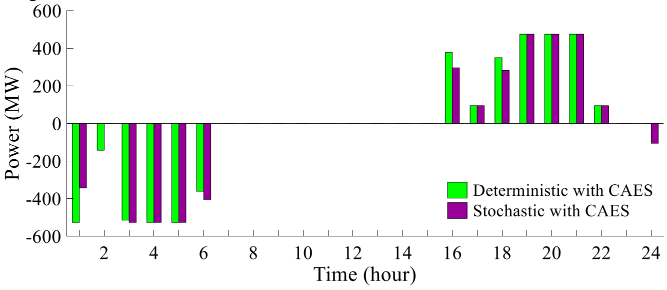

Fig. 6. The hourly operational state of CAES unit

The results of stochastic programming show that more expensive units must be committed to accommodate the uncertainties of loads and redress the imbalances of wind farms compared with the deterministic case. Therefore, the third scenario has the highest operational cost. In this scenario, the pessimistic scenarios are generated which incline the schedule to the probability of lower wind extraction. However, the incorporation of CAES unit has caused a considerable save in operation cost. The results of 4th scenario show that the utilization of CAES has enhanced the extraction of available wind generation and has decreased the expected generation cost. Besides, the expected cost of stochastic programming-based SCUC with CAES ($1876395) is similar to that of the deterministic case ($1841987) which indicates that inclusion of storage unit would help decrease the impact of uncertainties.

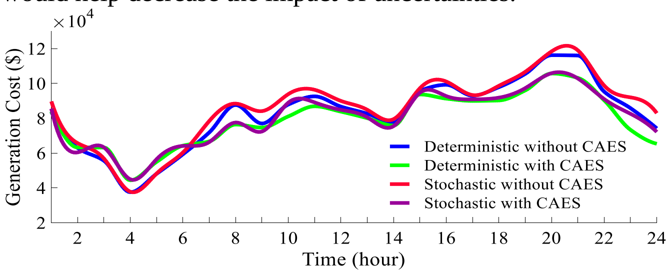

Fig. 7. The hourly generation cost

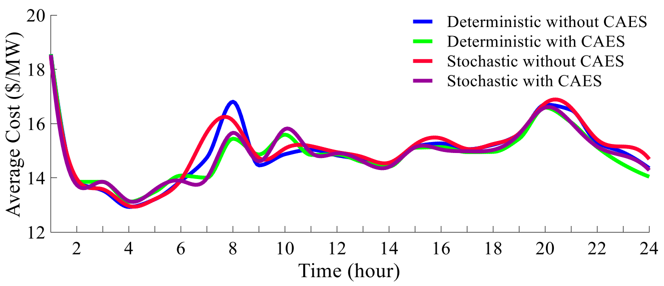

Fig. 8. The hourly average cost

As can be seen in Fig. 7, the scenarios with a storage unit have smoother generation cost and lower peak. In addition, the stochastic scenarios have higher generation costs compared with deterministic cases. As the wind energy is more available, the generation cost is more decreased. Fig. 8 represents that the average cost of the system without CAES is higher than the case of with presence of storage unit.

Table 8. The hourly spinning reserve cost in various scenarios

Time	**1**	**2**	**3**	**4**
Deterministic without CAES	4243.6	2819.3	2361.5	1520.6
Deterministic with CAES	4621.5	2891.6	2450.3	1566.4
Stochastic without CAES	3970.2	2754.9	2330	1518.9
Stochastic with CAES	4409.6	2878.9	2456.3	1551.5
Time	**5**	**6**	**7**	**8**
Deterministic without CAES	1934.4	2494.8	3156	4152
Deterministic with CAES	2024.6	2568.8	3058.2	3979.9
Stochastic without CAES	1932.6	2467.2	3274.9	3803.8
Stochastic with CAES	1989.4	2529.3	3066.4	4033.5
Time	**9**	**10**	**11**	**12**
Deterministic without CAES	3847.8	4129.4	4114.7	3808.1
Deterministic with CAES	4132.5	4771.2	4243.4	3943.6
Stochastic without CAES	3692.9	3998.8	4031.2	3735.2
Stochastic with CAES	4103	4563.5	4196.1	3920
Time	**13**	**14**	**15**	**16**
Deterministic without CAES	3553.4	3329.6	3962.5	4056.9
Deterministic with CAES	3610.8	3367.8	4019.3	4075.2
Stochastic without CAES	3503.2	3283.3	3939.1	4081
Stochastic with CAES	3600.2	3375.7	3989.1	4022.3
Time	**17**	**18**	**19**	**20**
Deterministic without CAES	3754.7	3998.5	4348.6	4909.4
Deterministic with CAES	3766.5	3957.4	4346.4	4951.8
Stochastic without CAES	3746.5	3980.9	4322.4	4853.2
Stochastic with CAES	3746.6	3971.2	4387.5	4947.7
Time	**21**	**22**	**23**	**24**
Deterministic without CAES	4996.2	4229.9	4159.8	3909.2
Deterministic with CAES	4938.9	4282.8	4431.3	4112.9
Stochastic without CAES	4921.5	4150.3	4020.7	3719.3
Stochastic with CAES	4947.2	4267.9	4230.6	4015.2

Regard to the reserve provision costs presented in Table 8, for a 24-hour period, the first scenario has the total reserve cost of $87791.88 based on the day-ahead spinning reserve market clearing price. The spinning reserve is supposed to be 10% of hourly load plus by 10% of penetrated wind power. The second scenario has a higher rate of reserve cost by $90114.44. The reason is that although the market clearing prices and average costs are lower than the first scenario, more wind power is penetrated in supplying demand which has caused the spinning reserve costs. The 3rd scenario has lower total reserve cost ($86033.02) in comparison with the first scenario because it has adopted a more risk-averse policy through stochastic SCUC and lower wind power could penetrate (see Fig. 5). Hence, lower reserve capacity is required, although it has the highest generation costs among all scenarios. In the last scenario, the CAES unit is integrated which has helped more penetration of wind resources. In this regard, more reserve capacity must be maintained in order to have a low-risk operation. Even though the more spinning reserve must be provided, but the total operation cost in this scenario is $89199.8 that is not too much higher than the third scenario. The reason why is that the exploitation of higher capacities of wind has decreased the average cost and the corresponding clearing price considerably which has alleviated the reserve cost.

According to the reports of U.S. energy information administration (EIA) [60], the price of saving each kWh electricity production from carbon-free resources rather than conventional thermal sources can be considerable. In this regard, 1 kWh of electricity, if generated from a fossil fuel burning conventional thermal power plant, will generate 0.94 kg CO_2. Other emissions such as NO_x, SO_2, CO are neglected. According to [61,62], the value of an emission reduction by 1 ton is equal with $33. With respect to the Table 7, the value of penetrated wind power can be presented as Table 9.

Table 9. The value of emission reduction by renewable penetration

scenario	Emission reduction (ton)	Value of emission prevention ($)
Deterministic without CAES	6307.4705	208146.5
Deterministic with CAES	11026.8298	363885.4
Stochastic without CAES	2716.3462	89639.42
Stochastic with CAES	9237.3847	304833.7

6. Conclusion

In this study, a stochastic model for security-constrained unit commitment problem is presented. The CAES unit is incorporated as a storage unit to mitigate the imbalances. The simulation is conducted on a standard IEEE 118-bus test system. The result of stochastic method will be obtained based on the generation of 1000 scenarios. The most probable scenario will be derived from all generated scenarios for each hour, each of which can be obtained from interaction between the probability of all kinds of uncertainties. The results show that inclusion of stochastic method will increase the operation cost. However, the system is more likely to keep its secure operation in case of volatilities and contingencies and can withstand unplanned or unforecasted changes. The incorporation of compressed air energy storage technology has helped the operator to increase the dispatchability of wind units and utilize more energy from uncertain resources. The storage units can store the excess potential of energy in case of congestion of transmission lines. As the results show, the generation costs of deterministic and stochastic approach are about $1841987 and $1876395 (± 9325) which are almost the same. This fact shows that inclusion of CAES has decreased the impact of uncertainties. The stochastic SCUC without CAES has the highest operational cost, which is about $2007979 (± 17675). In addition, an emission-oriented analysis is also presented.

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Appendix

Table 2.a. The characteristics of IEEE 188-bus 54-unit test system (Generators' data)

Unit	P_i^{min}	P_i^{max}	RDR_i	RUR_i	c_i	b_i	a_i
1	5	30	30	30	31.6710	26.24382022	0.069663
2	5	30	30	30	31.6720	26.24382022	0.069663
3	5	30	30	30	31.6730	26.24382022	0.069663
4	150	500	500	500	6.78010	12.88750000	0.010875
5	100	300	300	300	6.78020	12.88750000	0.010875
6	10	30	30	30	31.6740	26.24382022	0.069663
7	25	100	100	100	10.1510	17.82000000	0.012800
8	5	30	30	30	31.6750	26.24382022	0.069663
9	5	30	30	30	31.6760	26.24382022	0.069663
10	100	300	300	300	6.78030	12.88750000	0.010875
11	100	350	350	350	32.9610	10.76000000	0.003000
12	8	30	30	30	31.6770	26.24382022	0.069663
13	8	30	30	30	31.6780	26.24382022	0.069663
14	25	100	100	100	10.1520	17.82000000	0.012800
15	8	30	30	30	31.6790	26.24382022	0.069663
16	25	100	100	100	10.1530	17.82000000	0.012800
17	8	30	30	30	31.6711	26.24382022	0.069663
18	8	30	30	30	31.6721	26.24382022	0.069663
19	25	100	100	100	10.1540	17.82000000	0.012800
20	50	250	250	250	28.0010	12.32989708	0.002401
21	50	250	250	250	28.0020	12.32989708	0.002401
22	25	100	100	100	10.1550	17.82000000	0.012800
23	25	100	100	100	10.1560	17.82000000	0.012800
24	50	200	200	200	39.0010	13.29000000	0.004400
25	50	200	200	200	39.0020	13.29000000	0.004400
26	25	100	100	100	10.1570	17.82000000	0.012800
27	100	420	420	420	64.1610	8.339147142	0.010590
28	100	420	420	420	64.1620	8.339147142	0.010590
29	80	300	300	300	6.78040	12.88750000	0.010875
30	30	80	80	80	74.3310	15.47077253	0.045923
31	10	30	30	30	31.6741	26.24382022	0.069663
32	5	30	30	30	31.6741	26.24382022	0.069663
33	5	20	20	20	17.9510	37.69679245	0.028302
34	25	100	100	100	10.1580	17.82000000	0.012800
35	25	100	100	100	10.1590	17.82000000	0.012800
36	150	500	500	500	6.78050	12.88750000	0.010875
37	25	100	100	100	10.1511	17.82000000	0.012800
38	10	30	30	30	31.6751	26.24382022	0.069663
39	200	650	650	650	32.9620	10.76000000	0.003000
40	150	500	500	500	6.78060	12.88750000	0.010875
41	8	20	20	20	17.9520	37.69679245	0.028302
42	20	50	50	50	58.8110	22.94225564	0.009774
43	100	300	300	300	6.78070	12.88750000	0.010875
44	100	300	300	300	6.78080	12.88750000	0.010875
45	100	300	300	300	6.78090	12.88750000	0.010875
46	8	20	20	20	17.9530	37.69679245	0.028302
47	25	100	100	100	10.1521	17.82000000	0.012800
48	25	100	100	100	10.1531	17.82000000	0.012800
49	8	20	20	20	17.9540	37.69679245	0.028302
50	25	50	50	50	58.8120	22.94225564	0.009774
51	25	100	100	100	10.1551	17.82000000	0.012800

52	25	100	100	100	10.1551	17.82000000	0.012800
53	25	100	100	100	10.1551	17.82000000	0.012800
54	25	50	50	50	58.8130	22.94225564	0.009774

Table 2.b. The characteristics of IEEE 188-bus 54-unit test system (Generators' data)

Unit	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
MUT_i	1	1	1	4	2	1	1	1	1	2	3	1	1	1	1	1	1	1
MDT_i	1	1	1	3	2	1	1	1	1	2	2	1	1	1	1	1	1	1
Unit	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
MUT_i	1	2	2	1	1	2	2	1	3	3	2	1	1	1	1	1	1	4
MDT_i	1	2	2	1	1	2	2	1	2	2	2	1	1	1	1	1	1	3
Unit	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54
MUT_i	1	1	5	4	1	1	2	2	2	1	1	1	1	1	1	1	1	1
MDT_i	1	1	4	3	1	1	2	2	2	1	1	1	1	1	1	1	1	1

Table 2.c. The characteristics of IEEE 188-bus 54-unit test system (Generators' data)

Unit	1	2	3	4	5	6	7	8	9
SUC	1040	1040	1040	1440	1110	1040	1050	1040	1040
SDC	100	100	100	100	100	100	100	100	100
CST	1	1	1	3	1	1	1	1	1
Unit	10	11	12	13	14	15	16	17	18
SUC	1100	1100	1040	1040	1050	1040	1050	1040	1040
SDC	100	100	100	100	100	100	100	100	100
CST	1	1	1	1	1	1	1	1	1
Unit	19	20	21	22	23	24	25	26	27
SUC	1059	1100	1100	1050	1050	1100	1100	1050	1250
SDC	100	100	100	100	100	100	100	100	100
CST	1	1	1	1	1	2	2	1	2
Unit	28	29	30	31	32	33	34	35	36
SUC	1250	1100	1045	1040	1040	1030	1050	1050	1440
SDC	100	100	100	100	100	100	100	100	100
CST	2	1	1	1	1	1	1	1	3
Unit	37	38	39	40	41	42	43	44	45
SUC	1050	1040	1440	1400	1030	1045	1100	1100	1110
SDC	100	100	100	100	100	100	100	100	100
CST	1	1	3	3	1	1	1	1	1
Unit	46	47	48	49	50	51	52	53	54
SUC	1030	1050	1050	1030	1045	1050	1050	1050	1045
SDC	100	100	100	100	100	100	100	100	100
CST	1	1	1	1	1	1	1	1	1

Table 2.d. The characteristics of IEEE 188-bus 54-unit test system (Lines' data)

Line	from	to	X	Line	from	to	X	Line	from	to	X
L1	1	2	0.0999	L63	46	47	0.127	L125	79	80	0.0704
L2	1	3	0.0424	L64	46	48	0.189	L126	68	81	0.0202
L3	4	5	0.00798	L65	47	49	0.0625	L127	81	80	0.037
L4	3	5	0.108	L66	42	49	0.323	L128	77	82	0.0853
L5	5	6	0.054	L67	42	49	0.323	L129	82	83	0.03665

L6	6	7	0.0208	L68	45	49	0.186	L130	83	84	0.132
L7	8	9	0.0305	L69	48	49	0.0505	L131	83	85	0.148
L8	8	5	0.0267	L70	49	50	0.0752	L132	84	85	0.0641
L9	9	10	0.0322	L71	49	51	0.137	L133	85	86	0.123
L10	4	11	0.0688	L72	51	52	0.0588	L134	86	87	0.2074
L11	5	11	0.0682	L73	52	53	0.1635	L135	85	88	0.102
L12	11	12	0.0196	L74	53	54	0.122	L136	85	89	0.173
L13	2	12	0.0616	L75	49	54	0.289	L137	88	89	0.0712
L14	3	12	0.16	L76	49	54	0.291	L138	89	90	0.188
L15	7	12	0.034	L77	54	55	0.0707	L139	89	90	0.0997
L16	11	13	0.0731	L78	54	56	0.00955	L140	90	91	0.0836
L17	12	14	0.0707	L79	55	56	0.0151	L141	89	92	0.0505
L18	13	15	0.2444	L80	56	57	0.0966	L142	89	92	0.1581
L19	14	15	0.195	L81	50	57	0.134	L143	91	92	0.1272
L20	12	16	0.0834	L82	56	58	0.0966	L144	92	93	0.0848
L21	15	17	0.0437	L83	51	58	0.0719	L145	92	94	0.158
L22	16	17	0.1801	L84	54	59	0.2293	L146	93	94	0.0732
L23	17	18	0.0505	L85	56	59	0.251	L147	94	95	0.0434
L24	18	19	0.0493	L86	56	59	0.239	L148	80	96	0.182
L25	19	20	0.117	L87	55	59	0.2158	L149	82	96	0.053
L26	15	19	0.0394	L88	59	60	0.145	L150	94	96	0.0869
L27	20	21	0.0849	L89	59	61	0.15	L151	80	97	0.0934
L28	21	22	0.097	L90	60	61	0.0135	L152	80	98	0.108
L29	22	23	0.159	L91	60	62	0.0561	L153	80	99	0.206
L30	23	24	0.0492	L92	61	62	0.0376	L154	92	100	0.295
L31	23	25	0.08	L93	63	59	0.0386	L155	94	100	0.058
L32	26	25	0.0382	L94	63	64	0.02	L156	95	96	0.0547
L33	25	27	0.163	L95	64	61	0.0268	L157	96	97	0.0885
l34	27	28	0.0855	L96	38	65	0.0986	L158	98	100	0.179
L35	28	29	0.0943	L97	64	65	0.0302	L159	99	100	0.0813
L36	30	17	0.0388	L98	49	66	0.0919	L160	100	101	0.1262
L37	8	30	0.0504	L99	49	66	0.0919	L161	92	102	0.0559
L38	26	30	0.086	L100	62	66	0.218	L162	101	102	0.112
L39	17	31	0.1563	L101	62	67	0.117	L163	100	103	0.0525
L40	29	31	0.0331	L102	65	66	0.037	L164	100	104	0.204
L41	23	32	0.1153	L103	66	67	0.1015	L165	103	104	0.1584
L42	31	32	0.0985	L104	65	68	0.016	L166	103	105	0.1625
L43	27	32	0.0755	L105	47	69	0.2778	L167	100	106	0.229
L44	15	33	0.1244	L106	49	69	0.324	L168	104	105	0.0378
L45	19	34	0.247	L107	68	69	0.037	L169	105	106	0.0547
L46	35	36	0.0102	L108	69	70	0.127	L170	105	107	0.183
L47	35	37	0.0497	L109	24	70	0.4115	L171	105	108	0.0703
L48	33	37	0.142	L110	70	71	0.0355	L172	106	107	0.183
L49	34	36	0.0268	L111	24	72	0.196	L173	108	109	0.0288
L50	34	37	0.0094	L112	71	72	0.18	L174	103	110	0.1813
L51	38	37	0.0375	L113	71	73	0.0454	L175	109	110	0.0762
L52	37	39	0.106	L114	70	74	0.1323	L176	110	111	0.0755
L53	37	40	0.168	L115	70	75	0.141	L177	110	112	0.064
L54	30	38	0.054	L116	69	75	0.122	L178	17	113	0.0301
L55	39	40	0.0605	L117	74	75	0.0406	L179	32	113	0.203
L56	40	41	0.0487	L118	76	77	0.148	L180	32	114	0.0612
L57	40	42	0.183	L119	69	77	0.101	L181	27	115	0.0741
L58	41	42	0.135	L120	75	77	0.1999	L182	114	115	0.0104
L59	43	44	0.2454	L121	77	78	0.0124	L183	68	116	0.00405
L60	34	43	0.1681	L122	78	79	0.0244	L184	12	117	0.14
L61	44	45	0.0901	L123	77	80	0.0485	L185	75	118	0.0481
L62	45	46	0.1356	L124	77	80	0.105	L186	76	118	0.0544

Table 2.e. Forecasted wind speed for different wind farms

time	WF1	WF2	WF3
0	17.39049	16.62098	17.54889
1	15.72644	15.00605	17.18179
2	13.14873	12.99081	12.38652
3	10.26047	9.334547	10.22254
4	5.307271	5.756187	4.989222
5	3.905411	3.960728	4.595987
6	9.108147	10.33578	8.834344
7	13.58268	11.65174	11.73218
8	15.53689	13.93169	16.57583
9	16.47103	15.44864	19.02452
10	17.68056	14.87107	15.20355
11	13.53597	13.45816	14.27221
12	14.27267	13.13520	11.85698
13	12.97743	12.82117	9.261243
14	11.56471	12.62770	10.39189
15	7.825829	10.63925	9.054792
16	5.534443	7.456474	9.796645
17	5.448855	4.741876	7.298818
18	6.497873	4.833726	10.24698
19	7.810315	4.977468	11.71220
20	9.111338	6.131076	14.58742
21	8.954672	8.230696	16.21885
22	10.58639	11.98765	15.40782
23	14.49010	15.63758	16.54389
24	16.87980	17.35667	17.53820