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Flexible and robust security-constrained unit commitment in the presence of wind power generation uncertainty

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Abstract

Unreliable resources in conventional power systems have created new challenges for the users of these systems. These sources of production, including wind and solar sources, with a significant share in the power generation of many power systems, cause problems in the safe and stable operation of power systems due to uncertainty. Therefore, it is very important to provide a method or model for safe and stable operation of power systems. The main innovation of this paper is to present a new SCUC model to maximize the flexibility of the system along with reducing the operating cost in the form of a security constrained multi-level robust optimization problem in the presence of wind uncertainty sources. Also, a set of demand response programs and rapid response hybrid cycle units are used as sources of flexibility. Accordingly, the tolerable range of uncertainty and system slope reservation is developed with a low-cost combination and with the commitment to flexible covering resources. The desired optimization problem has been solved with the help of the NCCG algorithm and MILP method. The efficiency and reliability of this proposed model have been simulated and evaluated in IEEE 6-bus and 118-bus standard power systems, and the simulation results confirm the technical and economic efficiency of this model.

Keywords: SCUC, wind power generation, flexibility, robustness, multilevel optimization, demand response
2020 MSC: 90C17

1 Introduction

Countries are increasingly using renewable products. According to recent reports of the International Renewable Energy Agency (IRENA), developed countries have adopted long-term goals and roadmaps for the maximum operation of renewable resources [17, 32, 38]. The International Energy Agency (IEA) report in 2022 and the BloombergNEF project stated that the sun and wind must become the main sources of global energy by 2050 to achieve the goals of net zero emissions [5]. However, the increase in the penetration rate of Renewable Energy Sources (RES) production

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has raised two important problems of operation in future energy systems. The first problem is the uncertain behavior of RES and the second is the management of the effects of the variability of these resources, which causes the lack of slope and the removal of involuntary load.

Based on recent research, the flexibility of power systems to reduce the effects of RES variability is of interest to researchers, and the evaluation of exchange flexibility in various aspects including identification, measurement and development has been focused in many researches in recent years [28]. Some articles examine flexibility and slope capability [23, 27]. The authors of reference [40] propose online indices to quantify the flexibility of power systems in short-term operation. Likewise, references [41, 43] investigated domain deficiencies by introducing slope costs for participating units in increasing flexibility. Besides, some articles examined operational flexibility as new productions and reservations by examining related costs [31, 44]. Also, a number of articles addressed the flexibility of the proposed system using optimization methods [2]. Some recent researches, in order to find the tolerable range for RES changes in the conditions to guarantee the safe operation of the power system with a predetermined risk level, used various resources in the transmission network and demand side resources [3, 6, 15, 35, 42]. Thus, many studies have focused on the problem of Unit Commitment (UC) in the power system [11, 19, 33, 34]. Also, some references considered Drmand Recpoce Programs (DRP) and fast slope demand response programs as sources of flexibility [36]. Moreover, reference [11] investigated a Security Constrained Unit Commitment (SCUC) of production units in the presence of renewable energy sources such as wind farms. In addition, a scenario-based framework based on historical data is proposed. The units commitment for a future day is based on the actual data of wind farm generation with rotating storage at source [19]. In reference [36], a commitment program of reliable production units in the presence of Energy Storage Source (ESS) is solved based on a developed approach. A real-time SCUC strategy developed based on the decomposition-based framework considering transmission constraints is proposed in reference [10]. Furthermore, reference [21] proposed a hybrid model of hybrid cycle units using configuration-based and parameter-based models. A robust optimization technique in the presence of uncertainties caused by RERs to maximize the profit of a power system has been proposed in reference [16]. The main innovation of this paper is to present a new SCUC model to maximize the flexibility of the system along with reducing the operating cost in the form of a security constrained multi-level robust optimization problem in the presence of wind uncertainty sources. Also, the set of incentive-oriented and time-oriented demand response program and hybrid cycle units with quick response are used as sources of flexibility. In this regard, the tolerable range of uncertainty and system slope reservation is developed with a low-cost combination and with the commitment of flexible covering resources. The desired optimization problem has been solved with the help of NCCG algorithm and MILP method. The efficiency and reliability of this proposed model have been simulated and evaluated in IEEE 6-bus and 118-bus standard power systems, and the simulation results confirm the technical and economic efficiency of this model. This article is organized as follows: the second part discussed the flexibility with the proposed set of dynamic uncertainty. And the third part addressed the demand response program modeling and the proposed multi-mode configuration in Combined Cycle Units (CCUs). The fourth section developed solving the SCUC problem with a Nested Column and Constrained Generation (NCCG) algorithm. The fifth section is the review and analysis of the numerical results and the sixth section is the conclusion.

2 Uncertainty and sources of flexibility

This article uses the slope capacity of thermal units, quick response sources in addition to have also been used on the production and demand side to develop flexibility in operation of power systems optimizing problem. Usually, the net load curve range of changes has limit fixed points in the upper and lower limits, which can be entered as a decision variable in the SCUC problem based on historical data and probability distribution functions.

2.1 Dynamic uncertainty range

The dynamic uncertainty range is considered as a decision variable to reach the optimal conditions of system operation. Equation (2.1) assumed that this range can be adjusted in two directions, up and down ±95%, which statistically means that depending on the operating conditions, the range can be adjusted in different adjustable

$$S.t. \quad ND_{n,t} = L_{n,t} + \Delta N^u_{n,t} z^u_{n,t} - \Delta N^d_{n,t} z^d_{n,t} \qquad \forall n \in \Lambda,\ t \in T \tag{2.1}$$

intervals, for example, deviation up to 99% up and up to 90% down, where, $ND_{n,t}$ is the uncertain net load for the nth bus at time t is formulated using two binaries $Z^{u/d}_{n,t}$ variables that allow deviation around the predicted value $L_{n,t}$ with a predetermined fixed interval range $\Delta N^{u/d}_{n,t}$. The relevant constraints for the range of the uncertainty interval are defined for binary variables of uncertain net load are defined in the problem to express the dependence of binary variables, the non-occurrence of simultaneous upper and lower deviations, and determining the uncertainty budget [1, 13].

We can provide more flexibility in the upper and lower intervals of confidence intervals by applying more changes between consecutive operation intervals. By doing this, while increasing the flexibility, the reliability of the system is also optimized. In addition to the capacity of conventional resources, the encouraging-based demand response program for the production and Combined Cycle Unit (CCU) have been considered to cover uncertainties of load due to their special characteristics including fast ramping capability, high speed (start-up/shutdown) and their fast response time [14, 18, 39].

2.2 Modeling of combined cycle units

Combined cycle power plants with Combined Cycle Gas Turbine (CCGT) have low startup/shutdown cost, high startup/shutdown speed and suitable ramp rate [20]. The rapid start-up of CCGT with the appropriate slope enables the system operator to provide for unforeseen uncertainties [9, 24]. According to Figure 1, unlike conventional thermal units that have two on and off states, CCUs with multiple Combustion Turbines (CTs) and Steam Turbines (STs) may have different operating modes. Any combination of CT and GT is expressed as an operating mode. According to Table 1, there are 8 configuration modes, of which only mode number 7 is not possible and the other 7 modes of operation of the combined cycle unit [12, 14].

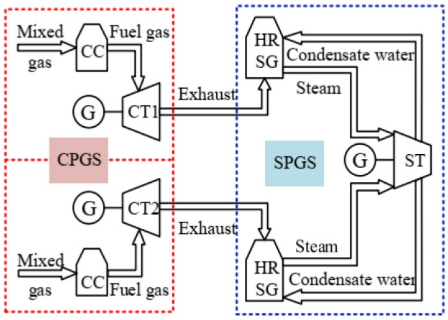

Figure 1: A Combined Cycle Unit configuration [14]

Table 1: Combined Cycle Unit configuration state

Condition	ST	CT2	CT1	State
Possible	0	0	0	0
Possible	0	0	1	1
Possible	0	1	0	2
Possible	1	0	1	3
Possible	1	1	0	4
Possible	0	1	1	5
Possible	1	1	1	6
Impossible	1	0	0	7

According to equation (2.2), a CCU with s components $I_s,\ s = 1 \in S$ can be introduced to show the state of the sth component in the mth Q_m configuration state [30].

$$Q_m = \prod I_1 I_2 ... I_s ... I_S \qquad i_s \in \{0, 1\} \tag{2.2}$$

i_s is a binary variable that shows the commitment status of the sth part. Then, if in m state, the sth part is online,

$I_s = i_s$ and otherwise if in mth state, sth part $I_s = 1 - i_s$ is offline. It will be like the linear equation (2.3):

$$\begin{aligned} &Q_m \le I_1 \\ &Q_m \le I_2 ... I_s ... I_S \\ &\quad \vdots \\ &Q_m \le I_s \\ &Q_m \ge \sum_{s=1}^{S} I_s - (S-1) \end{aligned} \tag{2.3}$$

where, Q_m is a continuous variable, means that the number of binary variables in the proposed commitment problem will not increase.

In each time interval, we will have 8 different combinations and the relationship between the combination of configuration states is not possible. For example, a steam turbine cannot be online unless one of the combustion turbines is online. States can be restricted to a number of possible transferable combinations. Figure 2 shows the different transition states between configuration states for a CCU unit with two combustion turbines and one steam turbine.

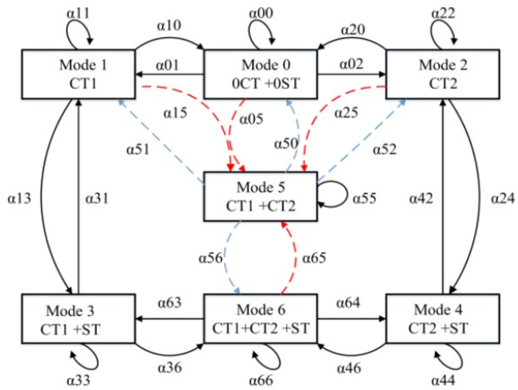

Figure 2: Analysis of the transition between the states of a hybrid cycle unit [24]

This limitation can be in the form of relation (2.4):

$$Q_{m,t-1} \le \sum_{n \in E_m} Q_{n,t-1} \tag{2.4}$$

in this equation, E_m is the set of possible states for the next time period for state m.

2.3 Modeling of demand response programs

Demand side management programs refer to the planning, implementation and monitoring activities of network administrators, independent network operators and retail network operators, during which consumers are encouraged to change their consumption patterns [25, 26].

This article examines the effects of the use of load response in the operating costs of the power system we will pay for this purpose, four different demand response programs under the titles of emergency demand response programs, ancillary service programs, time of use and Critical peak pricing are allowed to participate in both energy supply and reservation allocation. It should be noted that the sub-hourly reservation allocation of the demand response programs is only a suggested value to calculate the capacity of the demand response implementation on an hourly basis the previous day with higher accuracy. Demand Response Programs are briefly defined in the problem-solving formulation as DRs. For example, in relation (2.5), incentive payments are made as a reward for commitment in load reduction based on microeconomics with the demand-price elasticity equation [25]:

$$\begin{aligned} D_t &= D_t^0 \left\{ 1 - E_t \frac{Pr_t - Pr_t^0}{Pr_t^0} \right\} \\ E_t &= \frac{\partial D_t}{\partial Pr_t} \cdot \frac{Pr_t^0}{D_t^0} \end{aligned} \tag{2.5}$$

The amount of demand depends on changes in electricity tariffs. Therefore, according to relation (2.6), with the implementation of DR, the participating customers are motivated and receive rewards, and the reduced demand (CDt) is as follows:

$$C_t^{EDR} = -D_t^0 E_t \frac{inc_t^2}{Pr_t^0}, \qquad CD_t = -D_t^0 E_t \frac{inc_t}{Pr_t^0} \tag{2.6}$$

this equation defines the relationship between the incentive rate and the amount of load shedding. In this equation, inc_t is the equivalent cost, i.e. the product of limited demand and the incentive rate.

3 Robust optimal three-level problem with the commitment of flexible resources

As mentioned, this article is to design a new SCUC model to reduce the impact of wind power generation changes using a robust method with a dynamic proposed uncertainty interval. In addition, it considered maximum flexibility of the system with the commitment of CCUs and demand response program. Therefore, the robust three-level SCUC problem is proposed [8, 22]. In the first level of optimization according to relations (2.6) to (3.3), SCUC is solved as the external level for the base load state of the system through minimization and without considering the sources of uncertainty. As the second (intermediate) level, in equation (3.4), the worst case is extracted to realize the uncertainty of the net load in the problem by maximizing the operating conditions. In the third (internal) level, relations (3.5) to (3.8) are optimized once again in the form of production re-commitment decisions with the flexible resources commitment.

$$\min \sum_{t=1}^{T} \left\{ \sum_{i\in\Omega^{Tr}} \left(C_i^{Tr,SU} + x_{i,t} C_i^{Tr,NL} + c_i^{Tr} P_{i,t}^{Tr} + USC_i^{Tr} SP_{i,t}^{Tru} + DSC_i^{Tr} SP_{i,t}^{Trd} \right) + \sum_{n\in\Lambda^{EDR}} C_{n,t}^{EDR} + \sum_{n\in\Lambda^{EDR}} c_n^{EDR} ed_{n,t}^{u} \right\} \tag{3.1}$$

$$\sum_{i\in\Omega^{Tr}} P_{i,t}^{Tr} = \sum_{n\in\Lambda} NL_{n,t} - \sum_{n\in\Lambda} edrp_{n,t} \qquad \forall t\in T \tag{3.2}$$

$$-F_l^{\max} \le \sum_{n\in\Lambda} SF_{n,l} \left(\sum_{i\in\Omega_n^{Tr}} P_{i,t}^{Tr} - NL_{n,t} + edrp_{n,t} \right) \le F_l^{\max} \quad \forall l\in NL,\ t\in T \tag{3.3}$$

$$\Phi^{wc} = \max \left\{ \Phi \quad S.t. \quad ND_{n,t} = L_{n,t} + \Delta ND_{n,t}^{u0} z_{n,t}^{u} - \Delta N_{n,t}^{d0} z_{n,t}^{d} + \Delta_{n,t}^{u+} U_{n,t}^{+} - \Delta_{n,t}^{u-} U_{n,t}^{-} - \Delta_{n,t}^{d+} D_{n,t}^{+} + \Delta_{n,t}^{d-} D_{n,t}^{-} \right\}, \quad \forall n\in\Lambda,\ t\in T \tag{3.4}$$

$$\Phi = \min \left[\sum_{t\in T} \left\{ \sum_{n\in\Lambda} Voll_n (S_{n,t}^{+} + S_{n,t}^{-}) + \sum_{i\in\Omega^G} C_i^{G,NL} + c_i^G \sum_{m\in M} \Delta p_{g,t,m}^{G} \right\} \right] \tag{3.5}$$

$$\sum_{i\in\Omega^{T}} \Delta p_{i,t}^{Tr} + \sum_{g\in\Omega^G} \sum_{m\in M} \Delta p_{g,t,m}^{G} + \sum_{n\in\Lambda} (S_{n,t}^{+} + S_{n,t}^{-}) = \sum_{n\in\Lambda} ND_{n,t} - \sum_{n\in\Lambda} \Delta ed_{n,t}^{u} \quad \forall t\in T \tag{3.6}$$

$$-F_l^{\max} \le \sum_{n\in\Lambda} SF_{n,l} \left(\sum_{i\in\Omega_n^{T}} \Delta p_{i,t}^{Tr} + \sum_{g\in\Omega_n^{G}} \Delta p_{g,t}^{G} + S_{n,t}^{+} - S_{n,t}^{-} - ND_{n,t} + ed_{n,t}^{u} \right) \le F_l^{\max} \quad \forall l\in NL,\ t\in T \tag{3.7}$$

$$p_{g,y}^{G,\min} Q_{g,y,t} \le \Delta p_{g,y,t}^{G} \le p_{g,y}^{G,\max} Q_{g,y,t} \qquad \forall g\in\Omega^G,\ t\in T,\ y\in E_{g,m},\ m\in M_g \tag{3.8}$$

Objective function (3.1) includes thermal unit operation cost, unloaded thermal unit cost, loaded power production with thermal units costs, high and low reservation capacity allocation costs for thermal units, and demand response programs energy reservation costs. Relationship (3.2) relates to the balance of node power with the net load forecast with DR commitment in energy supply. Also, the power balance of the busbar constraint is mentioned using the sensitivity change coefficient matrixs (3.3). The middle maximum level in relation (3.4) tries to find the worst scenario for the lack of net load. The low minimum in relation (3.5) is a mixed integer decision -making problem. At this level, the commitment of the conventional producer units remains unchanged, and the units are re -balanced to reduce the impact of the worst conditions at the middle level, with the minimum commitment of quick response units.

Value of Lost Load (VOLL) can be used to evaluate the reliability of the system as an economic index in the SCUC problem to sustain the system in the manufacturing sector. The methods of calculating the unnecessary load clock are reviewed in the reference [7] and $1,000 is considered per megawatt while implementing the optimizing problem and establishing power balance equations at the system resilience boundary and the zero of VOLL. Relation (3.6) states that the cost of energy imbalances must be minimized. Relation (3.7) maintains the system's power balance in the event of the worst scenario. The constraint (3.8) is related to the flexibility provided by CCUS according to the different possible system configuration modes. Also for each CCU unit, a set of possible E_m transmission modes can be defined with $y \in E_m,\ m \in M_g$ components. More details of the conventional constraints of the SCUC optimization problem are available in the reference [30].

4 Problem solving with NCCG algorithm

The conventional CCG solving method is not applicable because low-level optimization decisions are a mixed integer problem and due to different CCUS configuration modes. Thus, in a NCCG three-level optimization framework, in relation to (4.1) constrained upper minimum levels (4.2) seeks a basic planning regardless of the uncertainties. In relation to (4.3), the middle maximum level seeks to find the worst scenario with the constraints (4.4) with the presence of the non-production of wind power at the predefined risk level. In relation to (4.5), the low minimum level also examines the lowest cost of operation by providing a solution for the worst scenario (4.6). Accordingly, the NCCG algorithm is used to confront non-convex binary variables in lower minimum level. Constraints are summarized in details in the references [29, 37].

Finally, the proposed model for solving the three -level optimization problem can be summarized as follows:

$$Obj_{upper} = \min_{x,p} c_b^T x + c_{gen}^T p \tag{4.1}$$

$$s.t. \qquad Ax + Bp \leq b \tag{4.2}$$

$$Obj_{middle} = \max_{\varepsilon \in U} h^T y \tag{4.3}$$

$$s.t. \qquad C\varepsilon \leq d \tag{4.4}$$

$$Obj_{lower} = \min_{y,z} h^T y \tag{4.5}$$

$$s.t. \qquad E(x,p,\varepsilon)y + F(x,p,\varepsilon)z \leq j \tag{4.6}$$

5 Simulate the proposed model in standard systems

In this section, the performance of the SCUC proposed model is simulated and evaluated in standard 6 and 118 IEEE systems. This is done for two modes with and without the presence of demand response resources and by applying the sources of rapid response hybrid cycle. The optimization problem is solved by the Mixed Integer Linear Program (MILP) model by CPLEX in GAMS software on a PC with Core i3 CPU processor and 4GB of RAM.

The long-term performance of the proposed model is compared with the results of Mont Carlo Simulation (MCS) [3]. Along with the upper level problem decision-making vectors, including the on/off status of thermal units, their corresponding production output in megawatt, and the power imbalance for each sample produced is calculated at a cost of 1000 mW/\$. The total cost is then defined as the total cost of operating the proposed SCUC model and the average cost of power imbalances in all samples and the total cost is compared to the definitive cost to evaluate the long-term performance. In all analyzes, the normalized budget of uncertainty (NBU) from NBU = 0.0 is performed in the most risky state to NBU = 1.0 in the most risk aversion.

5.1 The 6 busbar IEEE standard system

The system information is available in the reference [4] and its single -line diagram is presented in Figure 3. The production of wind farms is fluctuating depending on different weather conditions. The relatively precise prediction of wind production was determined in various ways and carried out in the relevant costs (megawatts of any busbar minus wind production). In this simulation, wind production capacity with an inflatable production capacity is 20% of the busbar load in the 4 and 5 busbars. The corresponding permissible range for these wind farms is [+20%, -20%] predicted values which is included in the calculations based on the assessment corresponding to the NBU normalized risk level percentage between 0% and 100%. Figure 4 shows the daily curve of the 6 busbar base system. In the multipurpose operation of the CCUs, the 2 units of the composite cycle with the maximum and the minimum production capacity of 25 MW and 5 MW with the same specifications each with two CTs and one ST used in busbars 2 and 6. Then, the SCUC problem for four different modes will be as follows.

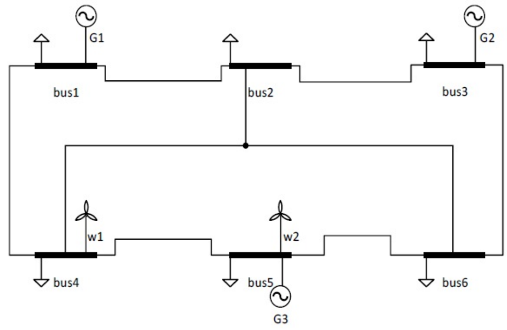

Figure 3: The 6 busbar system under study

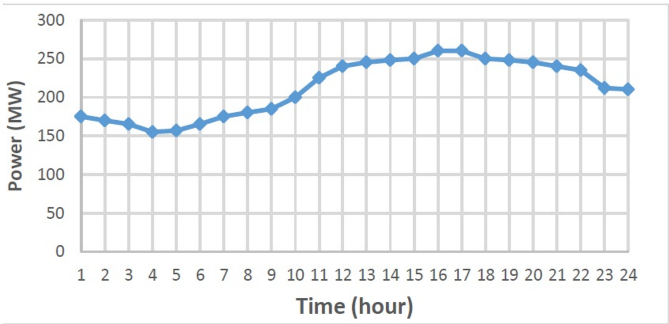

Figure 4: The 6 bus system under study base load

5.1.1 Investigating the SCUC problem with conventional and dynamic method without DR commitment

Figures 5 and 6 show the result of the long-term implementation of the proposed model corresponding to the various non-state budgets as the Number Budget of Uncertainty (NBU). These figures show that in both conventional and non-conventional methods, the cost of NBUS also increases the cost of SCUC and the extra cost is conservative. However, with the increase in NBUs, the cost of MCS fines sharply decreases as conservative strong decisions prevent violations of power balance for long-term programs. Figure 6 shows that in the proposed dynamic model, an optimal adaptation occurs in NBU = 0.2, which reduces the total cost to its lowest value, \$648806. In this case, no MCS violations will occur. Figure 7 shows the cost of retrofitting costs compared to NBU = 0 equivalent to \$6185 (\$642621-648806 = \$6185), which has increased by less than 1%, but the total cost has reduced to \$255566. Also, in the most conservative with NBU = 1.0, with \$25845 for retrofitting (equivalent to about 5% extra cost), this decision in the most risky case reduces the total cost of \$235906. This increase in overall cost confirms the acceptable performance of the proposed model in long -term implementation. In addition, comparing the dynamic and conventional method is observed, with the increase in NBU values, the costs of SCUC in dynamic uncertainty sets increase with more sloping sets. For example, in NBU = 0.2, the conservative cost of SCUC in the dynamic method is \$2079 more than the corresponding cost of the conventional uncertainty set (\$648806-\$ 646727 = \$2079). However, this additional cost can be justified by the long -term performance of the proposed dynamic model that optimized NBUs occur at NBU = 0.2 at a total cost of \$648806, which is \$1858 less than the optimal NBU for the conventional model. On the other hand, in the conventional way, optimized adaptation to a higher risk level in NBU = 0.4 at a total cost of \$ 650664 is obtained. Therefore, the proposed dynamic model, despite imposing a higher cost on conservatism, can do better in long-term programs.

5.1.2 Examine SCUC problem with conventional and dynamic method proposed with DR commitment

Now, we examine the impact of integration of DR program on SCUC costs and MCS costs. Figures 8 and 9 show that marginal prices are reduced by incentive payment by running DR for different NBU values. The reason for this is that the flexibility added by the DR program is due to the rapid slope capability, the lack of cost of starting and shutdowns with the frequent connection of these resources. Figure 8 shows that in the dynamic method, the cost value adaptation to the lowest cost is when NBU = 0.1 occurs. At this point, although the MCS is not the same as the optimal point of Figure 7, the cost of the SCUC and the total cost will decrease dramatically. As a result, the impact

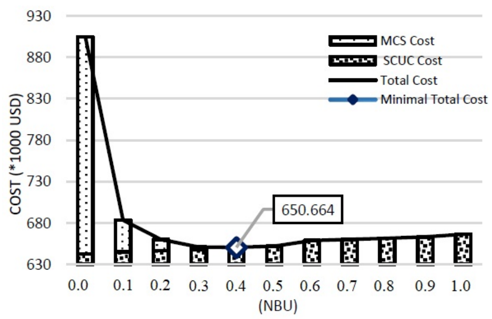

Figure 5: SCUC with conventional method without DR commitment

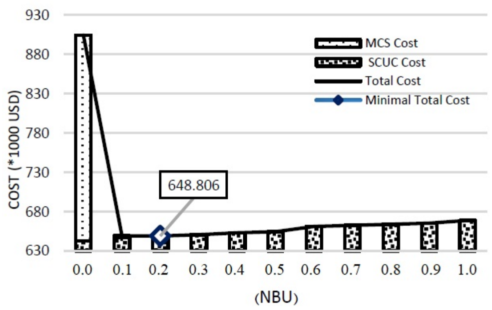

Figure 6: SCUC with proposed dynamic method without DR commitment

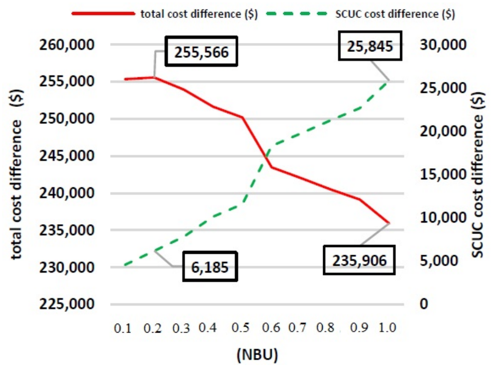

Figure 7: Comparison of retrofitting cost with total

of the DR is reduced from \$ 648806 in NBU = 0.2 dynamic method without implementation of DR to \$ 645830, which occurs while the optimal risk level of NBU is also reduced from 0.2 to 0.1. This shows that the final robust response is the best performance when the NBU is relatively small and can be justified by the central limit in probability studies [14].

In fact, it can be interpreted in this way that against the worst scenarios, it is possible to choose the appropriate level of uncertainty by using the law of probability as an indicator. Another important point is the share of DR, which is almost unchanged for all NBUs; because in DR, demand reduction is only based on incentives and no penalty is considered for non-committment. In fact, the DR source is acceptable and effective for almost all risk levels (i.e., different NBUs). In general assessment of Figures 10 and 11, it shows that the best optimized point of operation is the lowest cost of DR with the lowest cost and in the lowest budget, which indicates the superiority of the dynamic method with DR commitment. In the second place, the dynamic method without DR commitment, although it has a higher optimal cost than the dynamic method with the DR commitment, the conditions of operation will improve even without the accountability of demand than the conventional method of operation. The conventional method with DR commitment is in the third rank and shows the impact of DR on the cost of reducing costs. Finally, the conventional method without DR commitment shows that dynamic DR commitment has the lowest overall cost at \$ 645,830, which meets the lowest level of NBU = 0.1. While the conventional state optimization without DR commitment at a total cost of \$ 650,664 occurs in the NBU = 0.4 budget, which shows the superiority of the proposed dynamic method for covering uncertainties.

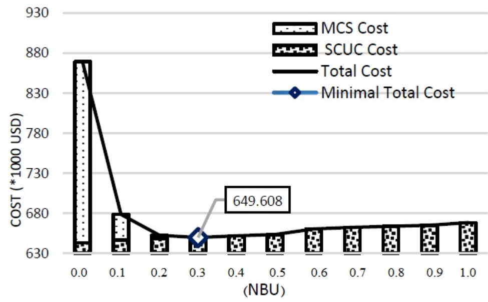

Figure 8: SCUC with conventional method with DR commitment

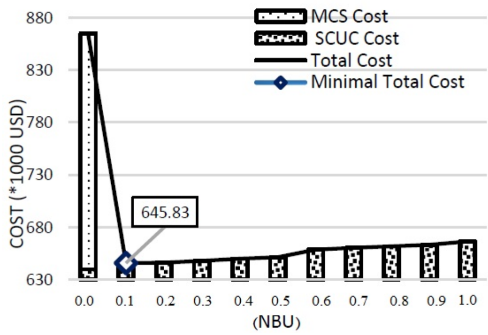

Figure 9: SCUC with proposed dynamic method with DR commitment

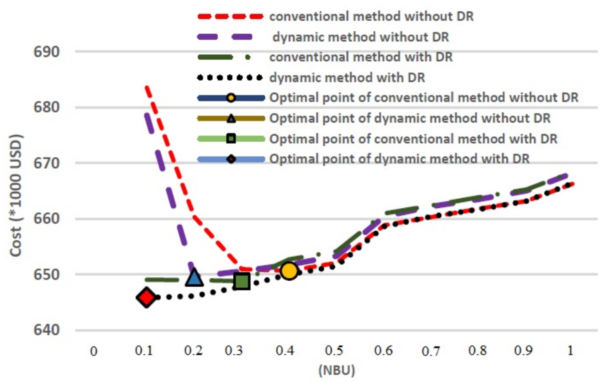

Figure 10: Investigation of the SCUC problem of the proposed conventional and dynamic method with and without DR commitment participation DR

The conventional method is \$ 648,806 with a total cost of \$ 648,806, which realizes the risk of NBU = 0.3. The dynamic method without DR's commitment also covers a total of \$ 649,608 at the risk level of NBU = 0.2. The impact of this work on reducing the commitment of expensive thermal units and consequently reducing the overall cost is clearly observed in the results and can be operated by optimizing the sustainable energy supply of high-income renewable resources in more flexible conditions in short-term operation.

5.2 The 118 busbar IEEE standard system

In this section, the proposed model is implemented on 118 busbar IEEE standard system, which contains 54 thermal units and 186 lines with 6600 MW peak load. In Multi-CCUs, out of 15 hybrid cycle units with maximum and minimum production capacity of 100 MW and 25 MW with the same specifications each installed with two CT

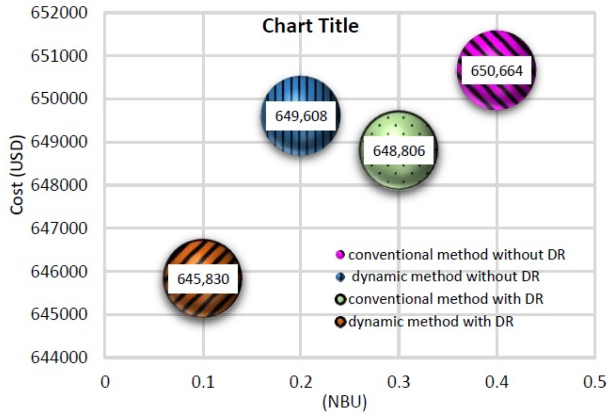

Figure 11: Comparison of the optimal adaptation of the proposed conventional and dynamic method with and without DR commitment

and one ST in busbars 18, 36, 36, 46, 55, 56, 62, 76, 77, 82, 104, 105, 111, 112, 113. Based on the configuration of the hybrid cycle units, we will have 105 possible combinations for different modes.

It is assumed that the wind sources of uncertainty in 10 high loaded busbars (11, 15, 49, 54, 56, 59, 62, 62, 80, 90) and each with a wind production capacity are 20% of the corresponding busbar load. The relevant range for these wind farms is between [%+20,%-20] values. The results of simulation of the conventional method and the proposed dynamic method are as follows with the long-term implementation of the SCUC problem solving in four different modes.

5.2.1 Examine the SCUC problem with conventional and dynamic method without DR commitment

First, the SCUC problem is proposed and solved in a dynamic method with the flexibility confidence and with the commitment of thermal units. As expected, in the long-term implementation, corresponding to the uncertainty budgets of wind production, which is considered to be NBUs, increases the cost of SCUC with increased NBUS. That justification for this added cost is related to the cost of conservative decision-making to cover the risk.

Figure 12 shows that with the increase in NBU, the cost of the penalty caused by the simulation of MCS to retrofitting the system is greatly reduced. Because, conservative strong decisions prevent power balance for long -term programs, so that from NBU = 0.2 onwards this value is zero and no penalty caused by MCS defects.

In NBU = 0.2, the optimum solution is created with the lowest total cost equivalent to \$ 1,975,436. However, compared to NBU = 0 mode with \$ 1,956,604, we will cost \$ 18,832, while the overall cost of the optimal point from \$ 2,753,564 to \$ 1,975,436 has reduced to \$ 2.9. Based on the central limit theory, Figure 13 shows that in costs percentages comparisons, 0.96% more costs in retrofitting using the dynamic method suggested to cover the uncertainties, can prevent 39.4% of the cost imposed in long-term operation. This is an acceptable performance in optimal resource commitment.

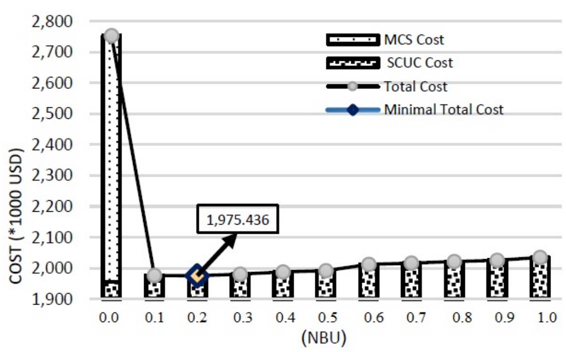

Figure 12: SCUC with dynamic method without DR commitment

It is also observed in the most conservative mode with NBU = 1.0 with 4% retrofitting cost, the overall cost in operational decision -making reduces by 35.29%. Although this is not an optimal point, this slight increase in SCUC

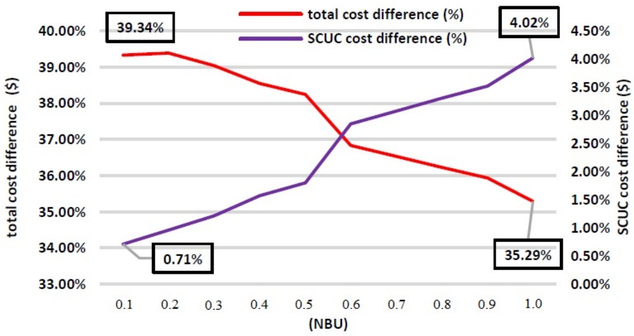

Figure 13: Comparison of the retrofitting cost and the total cost in the proposed dynamic method without DR commitment

shows acceptable performance in terms of security, confidence and efficiency of the system in providing and developing flexibility. Now the problem is modeled and implemented in both dynamic and conventional methods.

Figure 14 shows that with the increase in NBU values, the SCUC costs in dynamic state increased with a more relative slope than the set of conventional uncertainty. In the NBU = 0.2, the conservative cost for the dynamic method is \$ 1,975,436 and in the conventional method \$ 1,691,104. Although 0.3% higher cost (equivalent to \$ 6,332) is required in the corresponding cost of the budget of the complex, it has been more successful in reducing the overall cost of the dynamic method. In this way, while reducing the total cost, the optimal point also occurs at a lower risk level, which confirms the system's ability and dynamics to provide flexibility at the optimal point with the proposed method. However, as shown in Figure 14, this additional cost of risk aversion and retrofitting can be justified by reducing the overall cost of the optimal point, which confirms the acceptable performance of the proposed dynamic method with long-term programs.

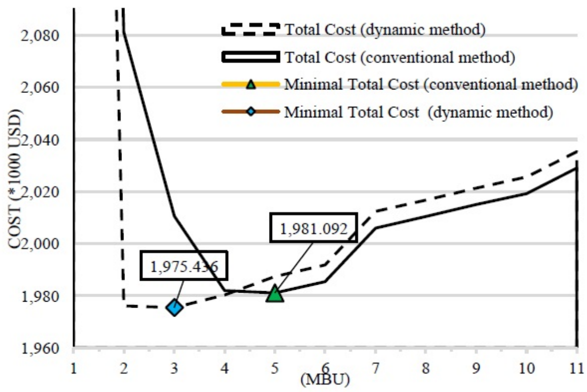

Figure 14: Examine different amounts of NBU costs without DR commitment

5.2.2 Examine the SCUC problem with conventional and dynamic method with DR commitment

Now this section analyzes the optimization implementation results, the impact of the DR demand response program on SCUC costs and MCS costs. Accordingly, through incentive payment, DR can reduce marginal prices not only during peak hours but also in non -peak hours. This can be justified by the fact that the flexibility added by the DR program is due to the fast slope capabilities and the lack of cost of startup and shutdown with the ability to use these resources repeatedly.

Figure 15 shows the lowest total cost in NBU = 0.1. At this point, the cost of the SCUC and the total cost are significantly reduced although the MCS is not zero like the previous optimal point.

In the NBU, due to the impact of the DR, the SCUC cost is reduced from \$ 1,975,436 to \$ 1,967,366, and at the optimal NBU point it has been reduced from \$ 1,975,436 to \$ 1,966,373.

In fact, when the DR is considered, the optimized NBU index is reduced from 0.2 to 0.1. DR commitment is an incentive and is not considered for non-commitment. In fact, the DR source is acceptable and effective for almost all risk levels (i.e., different NBUs). Figure 16 shows that the marginal price has also been stabilized in addition to reducing prices the marginal price of energy for high-profile busbars with and without DR commitment in the 24-hour time horizon at peak hours of demand. We also face reduced prices in non-peak hours, which is due to the coverage of the demand response program in the flexibility, and the fact that the DR has shown good performance both upward and downward by meeting the slope capacity. Figure 15 shows that SCUC cost, MCS cost and the total cost for all NBU values have been reduced with the implementation of the DR program, even in the conventional uncertainty set of values compared to the corresponding values in the previous section. However, the use of the flexibility added by the DR program, the optimal cost of $ 1,975,436 in the failure to run DR to $ 1,966,373, will reduce the cost of $ 9,063. But the optimized NBUs will be achieved if the cost section is added by the use of flexibility added by DR program. This means that, regardless of DR cost, decrease will be even more than $ 9,063.

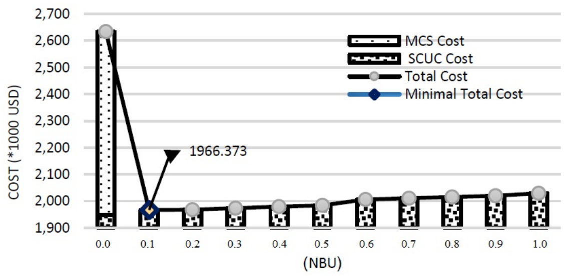

Figure 15: Examine the dynamic method with DR activation

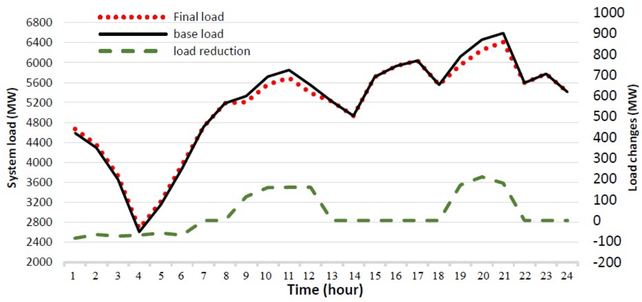

Figure 16: Examine the demand in the daily time horizon considering DR

Figure 17 shows that the conventional method also reduced the optimal cost compared to the decrease without DR commitment. The overall cost has fallen from $ 1,981,092 to $ 1,968,084, equivalent to $ 13,008, which saves the cost of favorable efficiency in the lack of conditions with the precise regulation of the flexibility and with the DR commitment. In addition, the optimal risk level in lower values for the definitions of the set of conventional and dynamic proposed settings is reduced from 0.2 to 0.1 in dynamic mode and from 0.4 to 0.3 in conventional mode. This shows that under the same conditions, the dynamic method is at the highest level of risk and is costly compared to the conventional method without activating the DR program.

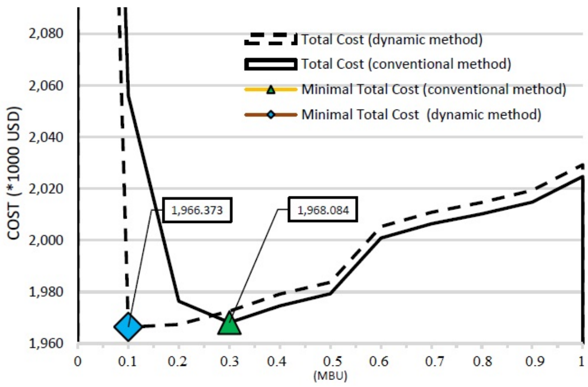

Figure 17: Examine the set of dynamic and conventional uncertainties with DR activation

Figure 18 shows that among the modes, the first optimized point of dynamic DR is the lowest cost and in the lowest budget, which indicates the dynamic superiority of the DR commitment and the optimal modeling of the Multi-mode CCUs. In the second rank the dynamic method without DR commitment, although with a higher optimal cost than the previous one, it shows that even without responsiveness, we will have better operation conditions than the conventional method. The conventional method with DR commitment is in the third rank and shows the impact of DR on the cost of reducing costs. The final one is the conventional method without DR commitment, which shows that conventional methods of non -dynamics in the flexibility range are lower than the dynamic method suggested in this article. Figure 19 shows that the dynamic mode with DR commitment has the lowest overall cost at \$ 1,966,373, which meets the lowest level of NBU = 0.1. While the optimization of the conventional state at a total cost of \$ 1,981,092 occurs in the NBU = 0.4 budget, which shows the superiority of the proposed dynamic method for covering uncertainties. The conventional method is \$ 1,968,084 with a total cost of \$ 1,968,084, which realizes the risk of NBU = 0.3. The dynamic method without DR's commitment also covers a total of \$ 1,975,436 at the risk level of NBU = 0.2. The impact of this work on reducing the commitment of expensive thermal units and following it reduced costs is clearly seen in the results. Units with uncertainty in more flexible conditions can work short-term operation by optimizing the system's sustainable energy supply.

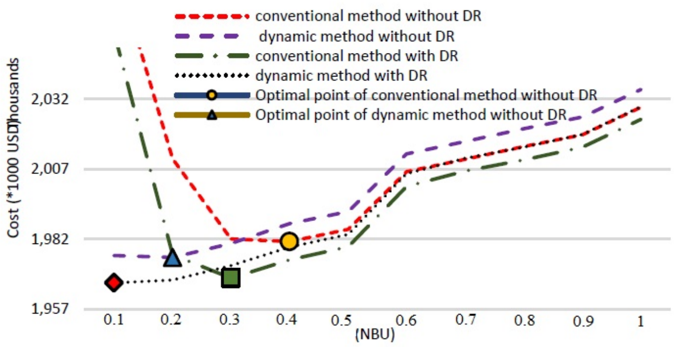

Figure 18: Evaluation of problem solving with and without the presence of DR by conventional and dynamic methods

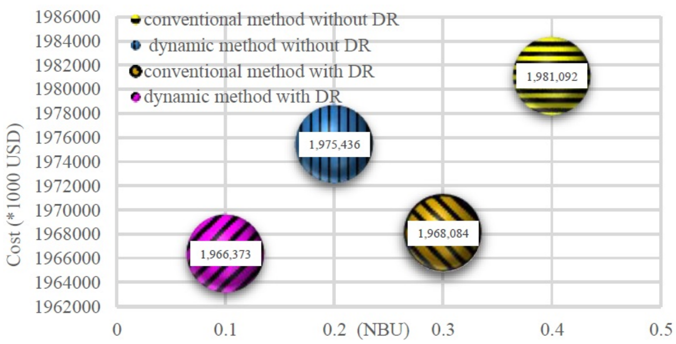

Figure 19: Comprehensive analysis of the uncertainty budget in different modes

5.2.3 Examine the effect of DR commitment on the SCUC problem in dynamic method

Since the most important factor in DR commitment is the total capacity permitted to participate in this program, Figure 20 shows different DR commitment capacities with a range of different values of NBU.

As expected, with the increase in the commitment rate of DR programs, the overall cost of operation will decrease dramatically. Reducing general costs from the most risk -taking with NBU = 0.1 to the most risk -aversion with NBU = 1.0 is shown in various commitments. This will clearly illustrate the impact of the DR commitment in the final cost. Examining the amount of cost reduction with DR implementation compared to its absence shows the optimal performance of the dynamic method use at DR presence. Overall, this sharp decline in costs can be interpreted by the inherent characteristics of the DR programs. Figure 21 shows that comparing the overall cost with 10% DR commitment is \$ 15,387, with 30% commitment, \$ 31,047 and 50% of \$ 46,479 in commitment.

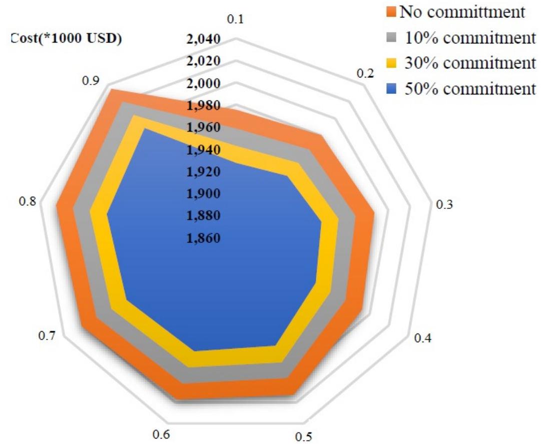

Figure 20: The effect of DR commitment in dynamic method

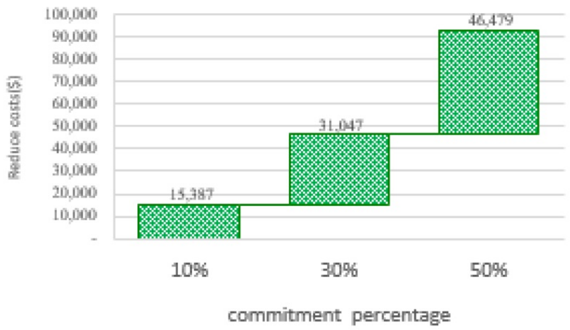

Figure 21: The effect of DR commitment

Figure 22 also shows each load response programs commitment percentage in peak hours. Accordingly, the time-based load response program had the highest load shift while the peak time pricing program had the most commitment in reducing the peak load.

The main reason for this is how the pricing of the time-oriented response program is to be priced. Because the price in the so-called valley times is far lower than the other two tariffs, namely non -peak hours and peak hours. However, the use of the peak pricing program is justified in the critical hours of the peak:

Time based (TOU): 39.7%

Incent based (EDRP): 23.8%

Ancillary services (ASD): 22.2%

Peak time pricing (CPP): 13.6%

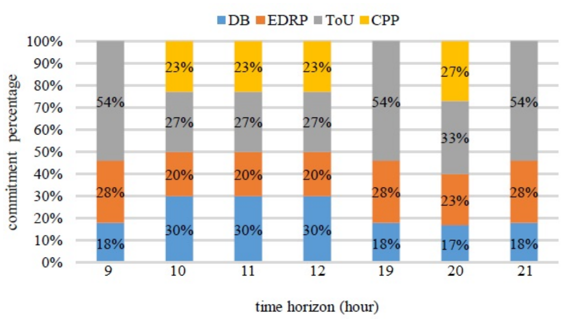

Figure 22: Commitment percentage per load response programs

The results infer that the long-term signaling of load response programs can direct investment. The reason for this rapid cost reduction includes:

- Absence of on and off costs on load response programs
- The rapid rate of changes in these programs without creating additional costs
- Reduced generator units premature slope capacity requirement
- Reduced the need to start the hybrid cycle generator unit to provide flexibility in a cross -sectional interval

The generator units must remain in the circuit by imposing extra costs on the circuit to cover the minimum limit.

6 Result

SCUC robust optimization was presented in a dynamic method to reduce the system operation cost in response to the renewable resources uncertainty. In the proposed model, changes in the confidence interval were entered into the SCUC problem by optimizing the decision variable. The optimal commitment of flexibility resources to cover the lack of conditions in wind production at the optimal risk level was as transactional flexibility between buyers and sellers. Although the cost of consolidation is added to the system, the proposed dynamic method of long -term use justifies the extra cost and the system was optimized as the risk level increases. On the other hand, the modern CCU units commitment and the implementation of the DR program, due to its agility and high slope capacity, increased the flexibility of the system under study. Multi-mode configuration of the SCUC decision -making units will include several optimized points that are solved by the proposed three-level optimization and compact integer planning and accurate NCCG algorithm. Besides, the overall cost of operation was significantly reduced with the implementation of the proposed model on standard 6 and 118 sample systems, which confirms the acceptable performance of the SCUC problem with the proposed dynamic method. Therefore, efficiency and improvement of operational conditions have clearly shown in two standard small and large systems.

References

[1] J.M. Alemany, D.C.A. Moitre, H. Pinto, and F. Magnago, *Short-term scheduling of combined cycle units using mixed integer linear programming solution*, Energy Power Engin. **5** (2013), 161–170.

[2] M.I. Alizadeh, M.P. Moghaddam, and N. Amjady, *Multistage multiresolution robust unit commitment with non-deterministic flexible ramp considering load and wind variabilities*, IEEE Trans. Sustain. Energy **9** (2017), no. 2, 872–883.

[3] M.I. Alizadeh, M. Parsa Moghaddam, and N. Amjady, *Flexibility contribution of heat ventilation and air conditioning loads in a multi-stage robust unit commitment with non-deterministic variability-oriented ramp reserves*, IET Gen. Transmis. Distrib. **12** (2018), no. 12, 3037–3045.

[4] D. Bertsimas, E. Litvinov, X.A. Sun, J. Zhao, and T. Zheng, *Adaptive robust optimization for the security constrained unit commitment problem*, IEEE Trans. Power Syst. **28** (2012), no. 1, 52–63.

[5] X. Chen, J. Layke, L.V.W. McGrory, J. Corfee-Morlot, and K. Kennedy, *Our solar future—Roadmap to mobilize USD 1 trillion by 2030*, WRI: World Resources Institute, U.S.A. 2022.

[6] R. Chen, J. Wang, A. Botterud, and H. Sun, *Wind power providing flexible ramp product*, IEEE Trans. Power Syst. **32** (2016), no. 3, 2049–2061.

[7] Cobos, N.G., J.M. Arroyo, N. Alguacil and A. Street, *Robust energy and reserve scheduling under wind uncertainty considering fast-acting generators*, IEEE Trans. Sustain. Energy **10** (2018), no. 4, 2142–2151.

[8] N.G. Cobos, J.M. Arroyo, N. Alguacil, and J. Wang, *Robust energy and reserve scheduling considering bulk energy storage units and wind uncertainty*, IEEE Trans. Power Syst. **33** (2018), no. 5, 5206–5216.

[9] J.J. Conti, P.D. Holtberg, J.A. Beamon, A.M. Schaal, J.C. Ayoub and J.T. Turnure, *Annual energy outlook 2014*, US Energy Info. Admin. **2** (2014).

[10] C. Dai, Y. Chen, F. Wang, J. Wan and L. Wu, *A configuration-component-based hybrid model for combined-cycle units in MISO day-ahead market*, IEEE Trans. Power Syst. **34** (2018), no. 2, 883–896.

[11] J. Dong, S. Han, X. Shao, L. Tang, R. Chen, L. Wu, C. Zheng, Z. Li and H. Li, *Day-ahead wind-thermal unit commitment considering historical virtual wind power data*, Energy **235** (2021), p. 121324.

[12] X. Fang, L. Bai, F. Li and B.-M. Hodge, *Hybrid component and configuration model for combined-cycle units in unit commitment problem*, J. Mod. Power Syst. Clean Energy **6** (2018), no. 6, 1332–1337.

[13] G. Ferrari-Trecate, E. Gallestey, P. Letizia, M. Spedicato, M. Morari, and M. Antoine, *Modeling and control of co-generation power plants: A hybrid system approach*, IEEE Trans. Control Syst. Technol. **12** (2004), no. 5, 694–705.

[14] D. Gielen, R. Gorini, R. Leme, G. Prakash, N. Wagner, L. Janeiro, S. Collins, M. Kadir, E. Asmelash, R. Ferroukhi, and U. Lehr, *World energy transitions outlook: 1.5° c pathway*, International Renewable Energy Agency (IRENA), 2021.

[15] E. Heydarian-Forushani, M.E. Hamedani Golshan, M. Shafie-khah, and P. Siano, *Optimal operation of emerging flexible resources considering sub-hourly flexible ramp product*, IEEE Trans. Sustain. Energy **9** (2017), no. 2, 916–929.

[16] B. Hu, L. Wu and M. Marwali, *On the robust solution to SCUC with load and wind uncertainty correlations*, IEEE Trans. Power Syst. **29** (2014), no. 6, 2952–2964.

[17] IRENA. *Roadmap 2030 Doubling the global share of renewable energy: a roadmap to 2030*, International Renewable Energy Agency, Working paper.

[18] F. Jabari, H. Arasteh, A. Sheikhi-Fini, H. Ghaebi, M.B. Bannae-Sharifian, B. Mohammadi-Ivatloo, and M. Mohammadpourfard, *A biogas-steam combined cycle for sustainable development of industrial-scale water-power hybrid microgrids: design and optimal scheduling*, Biof. Bioprod. Bioref. **16** (2022), no. 1, 172–192.

[19] K.-B. Kwon and D. Kim, *Enhanced method for considering energy storage systems as ancillary service resources in stochastic unit commitment*, Energy 213 (2020), 118675.

[20] E. Lannoye, D. Flynn, and M. O'Malley, *Assessment of power system flexibility: A high-level approach*, IEEE Power Energy Soc. Gen. Meet., IEEE, 2012, pp. 1–8.

[21] J. Li, S. Zhou, Y. Xu, M. Zhu and L. Ye, *A multi-band uncertainty set robust method for unit commitment with wind power generation*, Int. J. Electr. Power Energy Syst. **131** (2021), 107125.

[22] T. Limbu, T. Saha, and J. McDonald, *Value-based allocation and settlement of reserves in electricity markets*, IET Gen. Transmis. Distrib. **5** (2011), no. 4, 489–495.

[23] F. Lu, Z. Yu, Y. Zou, and X. Yang, *Energy flexibility assessment of a zero-energy office building with building thermal mass in short-term demand-side management*, J. Build. Eng. **50** (2022), 104214.

[24] B. Lu and M. Shahidehpour, *Short-term scheduling of combined cycle units*, IEEE Trans. Power Syst. **19** (2004), no. 3, 1616–1625.

[25] M.S. Misaghian, M. Saffari, M. Kia, A. Heidari, M. Shafie-khah, and J.P.S. Catalão, *Tri-level optimization of industrial microgrids considering renewable energy sources, combined heat and power units, thermal and electrical storage systems*, Energy 161 (2018), 396–411.

[26] F. Møller Andersen, S.G. Jensen, H.V. Larsen, P. Meibom, H. Ravn, K. Skytte, and M. Togeby, *Analyses of demand response in Denmark*, Risoe National Lab., 2006, No. RISO-R–1565 (EN).

[27] N. Navid and G. Rosenwald, *Market solutions for managing ramp flexibility with high penetration of renewable resource*, IEEE Trans. Sustain. Energy **3** (2012), no. 4, 784–790.

[28] N. Navid, G. Rosenwald and D. Chatterjee, *Ramp capability for load following in the MISO markets*, Midwest Indep. Syst. Oper. **20** (2011).

[29] B. Nitve and R. Naik, *Steady state analysis of IEEE-6 bus system using PSAT power toolbox*, Int. J. Eng. Sci. Innov. Technol. **3** (2014).

[30] N. None, *Annual energy outlook 2016 with projections to 2040*, USDOE Energy Information Administration (EI),

Washington, DC (United States), Office of Energy Analysis, No. DOE/EIA-0383, 2016.

[31] F. Pourahmadi, S.H. Hosseini, P. Dehghanian, E. Shittu and M. Fotuhi-Firuzabad, *Uncertainty cost of stochastic producers: Metrics and impacts on power grid flexibility*, IEEE Trans. Engin. Manag. **69** (2020), no. 3, 708–719.

[32] I.E.A. Renewables, *Analysis and Forecast to 2026*, International Energy Agency, Paris, France, 2021.

[33] S.P. Roukerd, A. Abdollahi, and M. Rashidinejad, *Uncertainty-based unit commitment and construction in the presence of fast ramp units and energy storages as flexible resources considering enigmatic demand elasticity*, J. Energy Storage **29** (2020), 101290.

[34] A.A. Salimi, A. Karimi, and Y. Noorizadeh, *Simultaneous operation of wind and pumped storage hydropower plants in a linearized security-constrained unit commitment model for high wind energy penetration*, J. Energy Storage **22** (2019), 318–330.

[35] S. Saranya and B. Saravanan, *Effect of emission in SMES based unit commitment using modified Henry gas solubility optimization*, J. Energy Storage **29** (2020), 101380.

[36] M.M. Serván, P.A. Aguirre and M.G. Marcovecchio, *Simultaneous optimal short term SCUC solution and power system redesign with real gap decomposition technique*, Comput. Chem. Eng. **150** (2021), 107338.

[37] S.S. Soman, H. Zareipour, O. Malik, and P. Mandal, *A review of wind power and wind speed forecasting methods with different time horizons*, North Amer. Power Symp., IEEE, 2010, pp. 1–8.

[38] E. Taibi, T. Nikolakakis, L. Gutierrez, C. Fernandez, J. Kiviluoma, S. Rissanen, and T.J. Lindroos, *Power system flexibility for the energy transition: Part 1, overview for policy makers*, Abu Dhabi, 2018.

[39] N. Troy, D. Flynn and M. O' Malley, *Multi-mode operation of combined-cycle gas turbines with increasing wind penetration*, IEEE Trans. Power Syst. **27** (2011), no. 1, 484–492.

[40] H. Wu, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, *Thermal generation flexibility with ramping costs and hourly demand response in stochastic security-constrained scheduling of variable energy sources*, IEEE Trans. Power Syst. **30** (2014), no. 6, 2955–2964.

[41] H. Wu, M. Shahidehpour, Z. Li and W. Tian, *Chance-constrained day-ahead scheduling in stochastic power system operation*, IEEE Trans. Power Syst. **29** (2014), no. 4, 1583–1591.

[42] H.B. Xiong, Y.H. Shi, Z. Chen, C. Guo and Y. Ding, *Multi-stage robust dynamic unit commitment based on pre-extended-fast robust dual dynamic programming*, IEEE Trans. Power Syst. **38** (2022), no. 3, 2411–2422.

[43] H. Ye, *Surrogate affine approximation based co-optimization of transactive flexibility, uncertainty, and energy*, IEEE Trans. Power Syst. **33** (2018), no. 4, 4084–4096.

[44] J. Zhao, T. Zheng and E. Litvinov, *Variable resource dispatch through do-not-exceed limit*, IEEE Trans. Power Syst. **30** (2014), no. 2, 820–828.