This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2019.2943311, IEEE Transactions on Smart Grid

Risk-Based Networked-Constrained Unit Commitment Considering Correlated Power System Uncertainties

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***Abstract*--The forecast errors for distributed energy resources (DERs) and hourly demands have contributed to power system uncertainties and additional risks in the day-ahead scheduling of electricity markets. In this paper, a risk-based approach is introduced to determine the stochastic solution of network-constrained unit commitment (NCUC) when additional uncertainties are embedded in the power system scheduling. The historical power market transaction data are used to model nodal injection uncertainties and reserve capacity requirements are considered to assess the solution of the risk-based NCUC. The proposed NCUC problem is formulated as a single-stage second order cone program which is a convex algorithm. The proposed approach provides an efficient solution for large-scale stochastic problems and helps accommodate the DER variabilities in secure and economic operations of power systems. The proposed stochastic algorithm is tested and the results are analyzed for the IEEE RTS-96 and IEEE 300-bus test systems.**

***Index Terms* -- Risk-based network-constrained unit commitment (NCUC), second-order cone programming, power system uncertainty.**

NOMENCLATURE

A. Sets and Indices

i,j	Index for market participants.
t, τ	Index for time periods.
G,D	Set of Generation and distribution companies.
Ψ_i	Feasible set of generating unit *i*.
$conv(\Psi_i)$	Convex hull of Ψ_i.

B. Variables

$b_i(t)$, $q_i^*(t)$	Price/quantity bid of participant *i* in period *t*.
$p_i^*(t), p_i(t)$	Transacted energy in the market and actual energy exchanged by participant *i* in period *t*.
$p_i^{pu}(t)$	Normalized actual production/consumption of participant *i* in period *t*.
$p_l^*(t), p_l(t)$	Predicted and actual power flow in transmission line *l* in period *t*.
$R(t)$	Required reserve capacity in period *t*.
$r_{dn}^*(t), r_{up}^*(t)$	Total negative/positive required ramping reserve in period *t*.
$r_{dn/up.i}^*(t)$	Negative/positive ramping allocation of generating unit *i* in period *t*.
$SW(t)$	Social welfare in period *t*.
$u_i(t)v_i(t)$	Binary variables indicating generating unit *i* starts up/shuts down in period *t*.
$x_i(t)$	Generating unit *i*'s commitment status in period *t*.
$w_i(t)$	Accepted bid of participant *i* in period *t*.
$z_R(t)$	auxiliary variable used in convex relaxation.
$\sigma_i(t), \sigma_R(t)$	RMSE of participant *i*'s power/required reserve capacity in period *t*.
$\sigma_l^{line}(t)$	RMSE of flow of line *l* in period *t*.

C. Parameters

C_i^{SU}, C_i^{SD}	Start-up/shut-down cost of generating unit *i*.
C_R^+, C_R^-	Cost of positive/negative reserve capacities.
k_i^l	Generation shift distribution factor of participant *i* corresponding to line *l*.
P_l^{Max}	Maximum capacity of transmission line *l*.
MU_i, MD_i	Minimum on/off hours of generating unit *i*.
P_i^{Min}, P_i^{Max}	Min/Max output power of generating unit *i*.
QS_i	Start-up/shut-down ramping capability of generating unit *i*.
RG_i	Down/up ramping capability of generating unit *i* when committed.
α_{dn}, α_{up}	Marginal factor of negative/positive reserve.
α_l	Marginal factor of transmission line *l*'s limit.

D. Matrices and Vectors

$\mathbf{COV}(t)$	Covariance matrix of $q_i^*(t)$.
$\mathbf{K}^l, \mathbf{Q}(t)$	Diagonal matrix of k_i^l and $q_i^*(t)$.
$\mathbf{W}(t)$	Variable vector of $w_i(t)$.
$(\mathbf{X})^T$, $\|\mathbf{X}\|_2$	Transpose and Euclidean norm of matrix **X**.
Diag(**X**)	Diagonal matrix whose diagonal values are vector **X**.

I. INTRODUCTION

THE penetration of variable energy resources together with the utilization of price sensitive loads have intensified supply and demand uncertainties in power systems. In such cases, system operators (SOs) have to use proper numerical tools to deal with uncertainties in the daily operation of power

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2019.2943311, IEEE Transactions on Smart Grid

systems. Among these tools, network-constrained unit commitment (NCUC) plays a significant role in providing robust decisions when SOs devise hourly schedules for maintaining the power system security in an uncertain environment. The complexity of the hourly NCUC solution will be heightened when generation and demand uncertainties are considered as the power system solution will require additional input data for the day-ahead scheduling. [1].

In the literature, numerous approaches are introduced for solving the NCUC problem when the proliferation of renewable energy is considered in power systems. These solution methods are categorized into deterministic and stochastic approaches. The deterministic approach which has been widely implemented in power systems provides the hourly commitment of generation resources in order to satisfy a predetermined load level and a conservative reserve requirement to respond to large contingencies such as the loss of the largest generator [2]. The deterministic approaches require fewer input data and impose less stringent computational burdens on large-scale systems. However, system uncertainties are not modeled in deterministic approaches which require a conservative level of reserve for managing the system security. Hence, deterministic approaches, which may result in economically-efficient UC decisions, do not guarantee that the system can withstand every probable scenario [3].

In contrast to deterministic approaches, stochastic NCUC relies on probabilistic models and stochastic optimization techniques to consider uncertainties in generation and demand [4]. Scenario-based and robust optimization techniques are commonly employed to solve the stochastic NCUC [5, 6]. In scenario-based approaches, probability distribution functions are fitted to uncertainty parameters of renewable power generation, price responsive loads, random network outages, etc. These distribution functions are used to generate uncertainty scenarios. Subsequently, the NCUC solution would maximize the expected social welfare while satisfying the pertaining system security constraints [7-11]. In this regard, the scenario-based NCUC can be formulated as multi-objective or risk-limiting optimization problems [12]. In the multi-objective formulation, maximizing social welfare and minimizing the cost/risk incurred by the uncertain behavior of the market participants are regarded as the objectives of the multi-objective optimization problem [7]. In the risk-limiting formulation the optimization is performed to maximize the social welfare subject while the system risk is limited in the constraints [13, 14]. It is also noteworthy that the accuracy and the complexity of scenario-based NCUC solutions depend on the quality and the number of scenarios. However, considering additional uncertain parameters would also require more scenarios to achieve a desired level of accuracy which could aggravate the complexity of NCUC and restrict its application to large-scale systems [15].

Robust optimization is another technique for solving the stochastic NCUC problem. In this approach, upper and lower bounds of uncertainties are considered to determine optimistic and pessimistic solutions that satisfy technical constraints [16, 17]. In comparison to the scenario-based NCUC method, the robust NCUC only requires a moderate level of information on uncertainty parameters which impose less computational burden to find the optimal solution. Besides, the approach produces UC decisions based on worst case scenarios and the attained schedule is immunized against uncertainties. However, the optimal generating unit schedule based on worst case scenario may not be economically optimal. In addition, the robust NCUC solution is very sensitive to the proposed intervals for uncertainty parameters [18].

Moreover, the correlated uncertainties in power systems ought to be considered in the operation and planning studies of energy systems. For instance, the air conditioning load and solar energy are highly correlated as they both are affected by solar irradiation. In this context, an uncertainty budget is considered in the robust solution of NCUC to restrict the joint variability of uncertain parameters [19], while the correlated nature of such parameters has seldom been modeled in the hourly scheduling of power systems. Authors in [20] also incorporate load and wind variability correlations in the robust optimization by considering a linear relationship between the load and wind. In the scenario-based NCUC, the correlation of uncertainties can be modeled theoretically by considering the joint probability distribution of uncertainties. For instance, variability correlations between wind speed and solar radiation are considered within the scenario sampling procedure in [21]. However, this approach would dramatically increase the required input data and computational complexity of the scenario-based NCUC solution which restrict its application to the operation of large-scale systems. Careful review of the existing works reveals that power system uncertainties have not thoroughly addressed correlations in NCUC studies.

Finally, NCUC is a large-scale, mixed integer, NP-hard optimization problem which ought to be solved efficiently for the daily economic and secure operation of power systems [22],[23]. In this regard, optimization techniques such as Benders decomposition [24] and progressive hedging [25, 26] have been implemented to enhance mathematical efficiency of the NCUC by breaking the large-scale problem into more tractable small-scale sub-problems [27]. Despite the past efforts, most of the available approaches impose high computational burdens to determine the NCUC solution which cannot guarantee its optimality in practical power system applications with the integration of large renewable energy resources [28, 29]. This paper will address such complexities by proposing a risk-based hourly NCUC solution which considers correlations.

A. *Contributions of the Paper*

Increasing the uncertainty among electricity producers and consumers introduces new challenges to power system operations. We have concentrated our efforts in this paper to develop new frameworks that can manage uncertainties associated with modern electricity producers and consumers. The main challenges of implementing conventional market mechanisms in electricity markets with high penetration of uncertain participants were discussed in our earlier work [30]. We also introduced a new approach in [31] to identify the optimal bidding strategy of a producer/consumer with highly uncertain production/consumption. Subsequently, a market design was proposed in [32] to manage uncertainties associated with market participation and facilitate the deployment of renewables into power systems. Finally, we have studies and analyzed power system operations with uncertain producers/consumers in emergency scenarios in [33].

In line with our previous works, this paper introduces a practical NCUC solution approach which maximizes the social welfare while satisfying technical constraints in an uncertain environment. In this regard, the reserve level is determined and allocated between the producers to compensate the uncertain behavior of the market participants. However, the random outages of the power system components have not been considered.

In the proposed approach, the individual and joint variabilities of power market participants are initially evaluated using historical wholesale market data which are incorporated into the solution of the NCUC problem. The corresponding optimization problem is modeled as a single-stage second order cone program (SOCP) which is a convex optimization and can be solved efficiently for large-scale power systems [34]. The main contributions of this paper are listed as follows:

- An analytical approach is introduced to assess the individual and joint uncertainties of power market participants using historical market transaction data.
- A stochastic formulation is proposed which incorporates individual and joint uncertainties in the solution of the NCUC problem.
- In the proposed approach, decision about the participation strategy of uncertain producers/consumers are made considering their bids/offers and associated reserve costs incurred to the system by their uncertain behavior.
- The proposed risk-based optimization model for the solution of NCUC problem is formulated as a single-stage SOCP which guarantees its practicality for calculating the hourly NCUC solution and applicability to large-scale power systems.

The rest of this paper is organized as follows. The general structure of the proposed approach is described and associated risk of market participants and required system's reserve are formulated in Section II. The NCUC problem is expressed in Section III and convex relaxation is conducted in Section IV. Numerical results are presented in Section V and conclusions are finally drawn Section VI.

II. General Structure of Proposed Algorithm

In restructured power systems, SO calculates the day-ahead schedule using offers/bids submitted by generation and distribution companies (Gencos/Discos). The SO applies NCUC to determine the optimal schedule of generating units that satisfies power system security constraints. However, real-time supply/demand of Gencos/Discos might deviate from the day-ahead schedule which cause uncertainties in the day-ahead schedule. Thus, the risk associated with market uncertainties should be considered as SO clears energy and reserve markets.

In power markets, Gencos (Discos) with higher levels of uncertainty should submit lower offer (higher bid) prices as they incur more reserves at additional system costs. Thus, the NCUC solution should consider submitted bids and offers along with the associated market risks of market participants in the day-ahead market. The outline of the proposed approach depicted in Fig. 1 incorporates uncertainty risks in the solution of the NCUC problem.

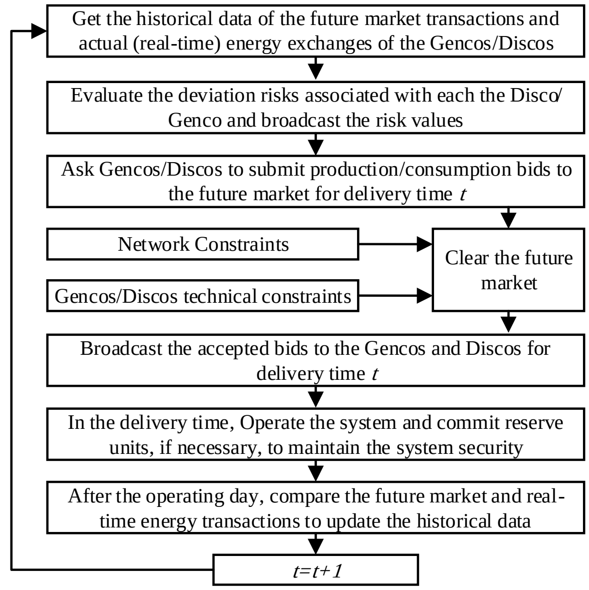

Fig. 1. Proposed framework for security-constrained unit commitment

In the proposed approach, the SO initially compares the historical data of market transactions to assess the associated solution risks pertaining to uncertainties. The SO will correspondingly accept participants' bids and offers for the day-ahead market in order to maximize the social welfare while maintaining the system security by allocating appropriate reserve capacity.

The participants' market trades are given as:

$$p_i^*(t) = w_i(t) \times q_i^*(t) \tag{1a}$$

$$0 \le w_i(t) \le 1 \tag{1b}$$

where $q_i^*(t)$ is offer/bid quantity submitted by Genco/Disco i, and $w_i(t)$ is the portion of the submitted offer/bid quantities that is accepted by the market. Here, $q_i^*(t)$ and $p_i^*(t)$ are positive values for generation and negative for loads. Accordingly, the market is operated so that:

$$\sum_i p_i^*(t) = 0 \quad \forall t \tag{2}$$

The actual energy procured by Gencos/Discos is modeled as a random variable $p_i(t)$. Thus, the reserve capacity for satisfying (2) is also a random variable, that is,

$$\sum_i p_i(t) + R(t) = 0 \quad \forall t \tag{3}$$

By combining (2) and (3), the required reserve capacity is written as:

$$\sum_i \left(p_i(t) - p_i^*(t)\right) = -\,R(t) \quad \forall t \tag{4}$$

Accordingly, $R(t)$ is a positive random variable if the system faces generation shortage and is a negative random variable otherwise. A rational SO would determine positive and negative system reserves such that the available capacities

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would be larger than $R(t)$ in every scenario. On this basis, the deviation of $R(t)$ from zero would determine the reserve capacity as a rational SO minimizes random deviations of $R(t)$ and the corresponding costs. In the following, the Root Mean Squared Error (RMSE) is applied to assess the required level of system reserve.

A. Evaluating RMSE of the Required Reserve

The RMSE of $R(t)$ is defined as:

$$\sigma_R^2(t) = E([R(t)-0]^2) = \frac{1}{t-1}\sum_{\tau=1}^{t-1}[R(\tau)-0]^2 = E\left(\left[\sum_{i=1}^{N}\left(p_i(t)-p_i^*(t)\right)\right]^2\right) = \sum_{i=1}^{N} E([p_i(t)-p_i^*(t)]^2) + 2\sum_{i=1}^{N}\sum_{j=i+1}^{N} E\left([p_i(t)-p_i^*(t)]\left[p_j(t)-p_j^*(t)\right]\right) \quad (5)$$

where the $\sigma_R^2(t)$ is mean squared error (MSE) and $\sigma_R(t)$ is the RMSE of $R(t)$. According to (5), $\sigma_R^2(t)$ consists of two terms. The first term is the sum of market participants' MSEs which measures the deviation of $p_i^*(t)$ from $p_i(t)$. The second term is the measure of joint variability of energy produced/consumed by Gencos/Discos.

B. Evaluation of Individual and Joint Variabilities

In this paper, the historical market transactions data has been implemented to evaluate individual and joint variabilities of the market participants. To compare day-ahead scheduling data, we normalize generation/load of Gencos/Discos as:

$$p_i^{pu}(t) = p_i(t)/p_i^*(t) \quad (6)$$

which demonstrates the randomness of the day-ahead schedule. In a perfect situation, $p_i^{pu}(t)$ will be equal to 1 and the MSE of $p_i^{pu}(t)$ is stated as:

$$\sigma_{i.pu}^2(t) = E\left(\left[p_i^{pu}(t)-1\right]^2\right) = \frac{1}{t-1}\sum_{\tau=1}^{t-1}\left[\frac{p_i(\tau)-p_i^*(\tau)}{p_i^*(\tau)}\right]^2 \quad (7)$$

By substituting (1a) in (7), the RMSE of $p_i(t)$ is :

$$\sigma_i(t) = \sqrt{E([p_i(t)-p_i^*(t)]^2)} = w_i(t)q_i^*(t)\sigma_{i.pu}(t) \quad (8)$$

Equation (8) shows the variabilities of Genco/Disco i. The RMSE of $R(t)$ also depends on the joint variability of generation/load. Hence, the covariance of $p_i^{pu}(t)$ and $p_j^{pu}(t)$ is defined as:

$$Cov_{i.j}^{pu}(t) = E\left(\left[\frac{p_i(t)-p_i^*(t)}{p_i^*(t)}\right]\left[\frac{p_j(t)-p_j^*(t)}{p_j^*(t)}\right]\right) = \frac{1}{t-1}\sum_{\tau=1}^{t-1}\left[\left[\frac{p_i(\tau)-p_i^*(\tau)}{p_i^*(\tau)}\right]\left[\frac{p_j(\tau)-p_j^*(\tau)}{p_j^*(\tau)}\right]\right]^2 \quad (9)$$

The covariance and correlation of $p_i(t)$ and $p_j(t)$ are:

$$Cov_{i.j}(t) = E\left([p_i(t)-p_i^*(t)]\left[p_j(t)-p_j^*(t)\right]\right) = (w_i(t)q_i^*(t))(w_j(t)q_j^*(t))\, Cov_{i.j}^{pu}(t) \quad (10)$$

$$Corr_{i.j}(t) = \frac{Cov_{i.j}^{pu}(t)}{\sigma_{i.pu}(t)\sigma_{j.pu}(t)} = \frac{Cov_{i.j}(t)}{\sigma_i(t)\sigma_j(t)} \quad (11)$$

Based on (8) and (10), RMSE of $R(t)$ is:

$$\sigma_R(t) = \sqrt{\sum_{i=1}^{N}\sigma_i^2 + 2\sum_{i=1}^{N}\sum_{j=i+1}^{N} Cov_{i.j}(t)} \quad (12)$$

The SO clears the day-ahead market (at time t) using the historical day-ahead market data for evaluating $\sigma_{i.pu}^2(t)$ and $Cov_{i.j}^{pu}(t)$ using (7) and (9), respectively. The SO calculates (8), (10) and (12) to evaluate $\sigma_R(t)$ for accepted bids and offers in day-ahead.

C. Reserve Capacity Assessment

The SO commits reserve units so that the available reserve capacity in every scenario is higher than $R(t)$. However, since the variability of $R(t)$ is often limited to a small number multiplies by RMSE, the reserve capacity is calculated as:

$$r_{up}^*(t) = \alpha_{up} \times \sigma_R(t) \quad (13)$$

$$r_{dn}^*(t) = \alpha_{dn} \times \sigma_R(t) \quad (14)$$

where $r_{up}^*(t)$ and $r_{dn}^*(t)$ are up/down reserve capacities. The power system risk is defined as the probability that the actual reserve capacity exceeds its committed value, which is stated as:

$$SR(t) = Prob(R(t) > r_{up}^*(t) \text{ or } R(t) < -r_{dn}^*(t)) \quad (15)$$

The SO could reduce the system risk by choosing higher values for α_{up} and α_{dn}. However, higher values would also increase the associated reserve costs.

III. Formulation of Risk-Based NCUC Problem

The objective function of the proposed NCUC problem is stated as:

$$Max \sum_{t}\sum_{i\epsilon D} w_i(t)(-q_i^*(t))b_i(t) - \sum_{t}\sum_{i\epsilon G}\left(w_i(t)q_i^*(t)b_i(t) + C_i^{SU}u_i(t) + C_i^{SD}v_i(t)\right) - \sum_{t}\left(C_R^+ r_{up}^*(t) + C_R^- r_{dn}^*(t)\right) \quad (16)$$

where the first term represents the revenues for energy sales to Discos and the second term represents the Gencos' production and start-up/shut-down costs. The associated costs of positive and negative reserve capacities are modeled in the last term. The proposed stochastic NCUC model is subject to (1), (2), (8)-(10), (12)-(14) and constraints associated with transmission flow and generating unit operation as presented next.

A. System Constraints

We apply a DC power flow in which the transmission flows have linear relations with the energy produced/consumed by market participants. Thus, the predicted and actual flow of line l are stated as:

$$p_l^*(t) = [k_1^l \cdots k_N^l] \times [p_1^*(t) \cdots p_N^*(t)]^T \quad (17)$$

$$p_l(t) = [k_1^l \cdots k_N^l] \times [p_1(t) \cdots p_N(t)]^T \quad (18)$$

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where k_1^l to k_N^l are generation shift distribution factors that solely depend on the network configuration. Hence, $p_l(t)$ is the weighted sum of random variables $p_i(t)$ and the RMSE of $p_l(t)$ is:

$$\sigma_l^{line}(t) = \sqrt{\sum_{i=1}^{N}(k_i^l)^2\sigma_i^2(t) + 2\sum_{i=1}^{N}\sum_{j=i+1}^{N}k_i^l k_j^l Cov_{i.j}(t)} \quad (19)$$

The transmission flow constraints are stated as:

$$-P_l^{Max} \le p_l^*(t) \pm \alpha_l \sigma_l^{line}(t) \le P_l^{Max} \quad \forall l, t \quad (20)$$

The generating unit constraints are:

$$-x_i(t-1) + x_i(t) - x_i(\tau) \le 0, \quad \forall i \in \forall t, \forall \tau \in \{t, \cdots, MU_i + t - 1\} \quad (21a)$$

$$x_i(t-1) - x_i(t) + x_i(\tau) \le 1, \quad \forall i \in G, \forall t, \forall \tau \in \{t, \cdots, MD_i + t - 1\} \quad (21b)$$

$$-x_i(t-1) + x_i(t) - u_i(t) \le 0 \quad \forall i \in G, \forall t \quad (21c)$$

$$x_i(t-1) - x_i(t) - v_i(t) \le 0 \quad \forall i \in G, \forall t \quad (21d)$$

$$p_i^*(t) + r_{up.i}^*(t) \le P_i^{Max} x_i(t) \quad \forall i \in G, \forall t \quad (21e)$$

$$P_i^{Min} x_i(t) \le p_i^*(t) - r_{dn.i}^*(t) \quad \forall i \in G, \forall t \quad (21f)$$

$$p_i^*(t) + r_{up.i}^*(t) - p_i^*(t-1) + r_{dn.i}^*(t-1) \le x_i(t-1)RG_i + (1 - x_i(t-1))QS_i \quad \forall i \in G, \forall t \quad (21g)$$

$$p_i^*(t-1) + r_{up.i}^*(t-1) - p_i^*(t) + r_{dn.i}^*(t) \le x_i(t)RG_i + (1 - x_i(t))QS_i \quad \forall i \in G, \forall t \quad (21h)$$

$$\sum_{i \in G} r_{dn.i}^*(t) \ge r_{dn}^*(t). \sum_{i \in G} r_{up.i}^*(t) \ge r_{up}^*(t) \quad \forall i \in G, \forall t \quad (21i)$$

where (21a)-(21b) represent the generating unit min on/off time; (21c)-(21d) represent start-up and shut-down status of generating units; capacity constraints are shown in (21e)-(21f); ramping constraints are enforced in (21g)-(21h); and (21i) indicates the total positive and negative reserve capacity of the system should be more than the required reserve.

The optimization model for the stochastic NCUC is a mixed integer and non-convex optimization problem. We develop a second order conic relaxation of the NCUC problem in the next section which is computationally tractable and practical for large-scale stochastic problems. It is noteworthy that large-scale convex SOCP problems can be efficiently solved with available software packages.

IV. Convex Relaxation of the Proposed NCUC Model

In this section, a convex relaxation approach is implemented to eliminate binary variables and nonlinear constraints (10), (12) and (19) are reformulated to convert the nonlinear NCUC to a SOCP problem which is much easier to solve.

A. *Convex Relaxation of Generating Unit Feasible Set*

The algorithm proposed in [35, 36] is applied to convert binary decision variables to continuous variables in which case the feasible set of each generating unit is substituted by its convex hull. The feasible set of generating unit i is stated as:

$$\psi_i = \{p_i^*(t), r_{up.i}^*(t), r_{dn.i}^*(t) \epsilon \mathbb{R}; \; x_i(t), u_i(t), u_i(t) \epsilon \{0.1\} | (21a) - (21i)\} \quad (22)$$

In order to reach the convex hull of the feasible set ψ_i, many inequalities are to be embedded which makes the problem intractable. To address this issue, we utilize a tractable approximation of convex hull of ψ_i [35] and consider the following inequalities to construct a tractable approximation of convex hull for generating unit i.

$$p_i^*(t-1) + r_{up.i}^*(t-1) \le QS_i x_i(t-1) + (P_i^{Max} - QS_i)(x_i(t) - u_i(t)) \quad \forall i \in G, \forall t \quad (23a)$$

$$p_i^*(t) + r_{up.i}^*(t) \le P_i^{Max} x_i(t) - (P_i^{Max} - QS_i)u_i(t) \quad \forall i \in G, \forall t \quad (23b)$$

$$p_i^*(t) + r_{up.i}^*(t) - p_i^*(t-1) + r_{dn.i}^*(t-1) \le (P_i^{Min} + RG_i)x_i(t) - P_i^{Min} x_i(t-1) - (P_i^{Min} + RG_i - QS_i)u_i(t) \quad \forall i \in G, \forall t \quad (23c)$$

$$p_i^*(t-1) + r_{up.i}^*(t-1) - p_i^*(t) + r_{dn.i}^*(t) \le -(P_i^{Min} + RG_i - QS_i)u_i(t) - (QS_i - RG_i)x_i(t) \quad \forall i \in G, \forall t \quad (23d)$$

$$conv(\psi_i) = \{p_i^*(t), r_{up.i}^*(t), r_{dn.i}^*(t) \epsilon \mathbb{R}; \; x_i(t), u_i(t), u_i(t) \epsilon \mathbb{R}^+ | (21a) - (21i). (23a) - (23d)\} \quad (23e)$$

where (23a)-(23d) tighten the feasible set ψ_i so that $conv(\psi_i)$ in (23e) is the approximation of the smallest convex set that contains ψ_i. In [37], it is proved that how constraints (23a)-(23d) give a tighter description of feasible schedules for generating units. Accordingly, the binary variables are regarded as continuous if (23a)-(23d) are embedded in the proposed NCUC approach [38]. By implementing this tight relaxation, the optimal value of relaxed binary variables will be close to integer solutions.

B. *Second Order Conic Formulation of the Proposed NCUC*

By substituting binary variables with continuous variables, (10), (12) and (19) would be the only nonlinear constraints. These nonlinear constraints are reformulated as a second order cone. In this regard, the non-linear constraints are represented as matrices and converted to a second order cone.

1) *Matrix representation of nonlinear constraints*

Assume $\mathbf{COV}(t)$, $\mathbf{Q}(t)$, $\mathbf{K}^l$ and $\mathbf{W}(t)$ are defined as below:

$$\mathbf{COV}(t) = \begin{bmatrix} Cov_{1.1}^{pu}(t) & \cdots & Cov_{1.N}^{pu}(t) \\ \vdots & \ddots & \vdots \\ Cov_{N.1}^{pu}(t) & \cdots & Cov_{N.N}^{pu}(t) \end{bmatrix} \quad (24)$$

$$\mathbf{Q}(t) = \text{Diag}([q_1^*(t) \quad \cdots \quad q_N^*(t)]) \quad (25)$$

$$\mathbf{K}^l = \text{Diag}([k_1^l \quad \cdots \quad k_N^l]) \quad (26)$$

$$\mathbf{W}(t) = [w_1(t) \quad \cdots \quad w_N(t)]^T \quad (27)$$

Consequently, $\sigma_R(t)$ and $\sigma_l^{line}(t)$ can be written as:

$$\sigma_R(t) = \sqrt{\mathbf{W}(t)^{\boldsymbol{T}}\mathbf{Q}(t)\mathbf{COV}(t)\mathbf{Q}(t)\mathbf{W}(t)} \quad (28)$$

$$\sigma_l^{line}(t) = \sqrt{\mathbf{W}(t)^{\boldsymbol{T}}\mathbf{K}^l\mathbf{Q}(t)\mathbf{COV}(t)\mathbf{Q}(t)\mathbf{K}^l\mathbf{W}(t)} \quad (29)$$

where $\mathbf{W}(t)$ are decision variables while $\mathbf{Q}(t)\mathbf{COV}(t)\mathbf{Q}(t)$ and $\mathbf{K}^l\mathbf{Q}(t)\mathbf{COV}(t)\mathbf{Q}(t)\mathbf{K}^l$ are known matrices when the SO clears the day-ahead market. By implementing the Cholesky decomposition [39], the matrices are decomposed as:

$$\mathbf{Q}(t)\mathbf{COV}(t)\mathbf{Q}(t) = (\boldsymbol{C_R}(t))^T \boldsymbol{C_R}(t) \tag{30}$$

$$\mathbf{K}^l\mathbf{Q}(t)\mathbf{COV}(t)\mathbf{Q}(t)\mathbf{K}^l = (\boldsymbol{C_l}(t))^T \boldsymbol{C_l}(t) \tag{31}$$

Subsequently, $\sigma_R(t)$ and $\sigma_l^{line}(t)$ are reformulated as:

$$\sigma_R(t) = \sqrt{\left(\boldsymbol{C_R}(t)\mathbf{W}(t)\right)^T\left(\boldsymbol{C_R}(t)\mathbf{W}(t)\right)} = \|\boldsymbol{C_R}(t)\mathbf{W}(t)\|_2 \tag{32}$$

$$\sigma_l^{line}(t) = \sqrt{\left(\boldsymbol{C_l}(t)\mathbf{W}(t)\right)^T\left(\boldsymbol{C_l}(t)\mathbf{W}(t)\right)} = \|\boldsymbol{C_l}(t)\mathbf{W}(t)\|_2 \tag{33}$$

According to (32) and (33), , $\sigma_R(t)$ and $\sigma_l^{line}(t)$ are represented as the Euclidean norm.

2) Second Order Cone Formulation

The proposed formulation of NCUC presented as SOCP has a linear objective and constraints together with inequality constraints stated in the form of Euclidean norm. So, by substituting (33) in (20), transmission constraints are converted to inequality constraints in the form of Euclidean norm. The proposed formulation is a SOCP problem if the nonlinear equality constraints (32) are reformulated as inequality constraints. So, auxiliary variables $z_R(t)$ are used and the proposed NCUC problem which is reformulated as:

$$\begin{aligned} Max \quad & \sum_t \sum_{i\epsilon D} w_i(t)(-q_i^*(t))b_i(t) \\ & - \sum_t \sum_{i\epsilon G} \left(w_i(t)q_i^*(t)b_i(t) + C_i^{SU}u_i(t) + C_i^{SD}v_i(t)\right) \\ & - \sum_t \left(C_R^+\alpha_{up} + C_R^-\alpha_{dn}\right)z_R(t) \end{aligned} \tag{34}$$

subject to:

$$\sigma_R(t) = \|\boldsymbol{C_R}(t)\mathbf{W}(t)\|_2 \le z_R(t) \quad \forall t \tag{35}$$

$$-P_l^{Max} \le p_l^*(t) \pm \alpha_l\|\boldsymbol{C_l}(t)\mathbf{W}(t)\|_2 \le P_l^{Max} \quad \forall l,t \tag{36}$$

and linear constraints (1), (2), (13), (14), (17), (21), and (23).

In the above formulation, equality constraints (32) are converted to inequality constraints (35) using $z_R(t)$. In the optimum solution, $z_R(t)$ take their lowest feasible values which are defined by (35). Thus, $z_R(t)$ is equal to $\sigma_R(t)$ in the optimal solution.

V. Implementation

To demonstrate the merits and applicability of the proposed risk-based NCUC approach, the proposed methodology is implemented on the IEEE RTS-96 and IEEE 300-bus test systems to clear an hourly day-ahead market. The computations are run on an Intel® Xeon® with 3.50 GHz process clocking and 32 GB of RAM by using the solver Gurobi 7.5.1.

A. IEEE RTS-96 test system

The IEEE RTS-96 test system contains 73 buses, 96 generating units, and 120 transmission lines. To study the effect of uncertain generation and demand, 6 wind power producers with a total installed capacity of 7,200 MW and 3 uncertain load points with a total demand of 4,500 MW are added to the system. The capacities, submitted bid prices, associated RMSEs of generating units and customers are summarized in [40].

1) Performance of the Proposed Risk-Based NCUC

In this section, the performances of deterministic and stochastic approaches are compared with that of the proposed risk-based model. We consider the following cases:

- Case 1: Deterministic SCUC with the required reserve is set to the largest generating unit (400MW).
- Case 2: Deterministic SCUC with the required reserve is set based on the NREL 3+5% rule.
- Case 3: Stochastic SCUC with SR(t) ≤ 0.01
- Case 4: Proposed risk-based SCUC with SR(t) ≤ 0.01

It is assumed that the SO determines the level of reserve in Cases 3 and 4 to maintain SR(t) below 1%. Accordingly, the operation in the day-ahead market is simulated and the committed reserve, associated system risks, social welfare, and reserve costs are compared in Figs. 2 and 3. The stochastic NCUC with SR(t)<0.01 is a two-stage stochastic NCUC (scenario-based) model such that in the first stage, the traded with market participants as well as allocated reserves are determined while in the second stage, considering the reserve capacity calculated in the first stage, the power

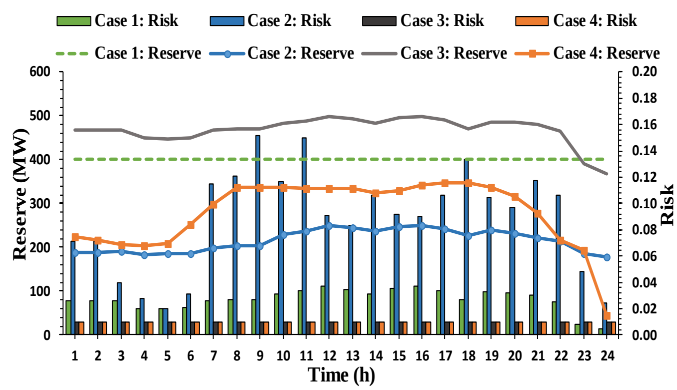

Fig. 2. Operating reserve and risk of the proposed approach and the benchmark settlements

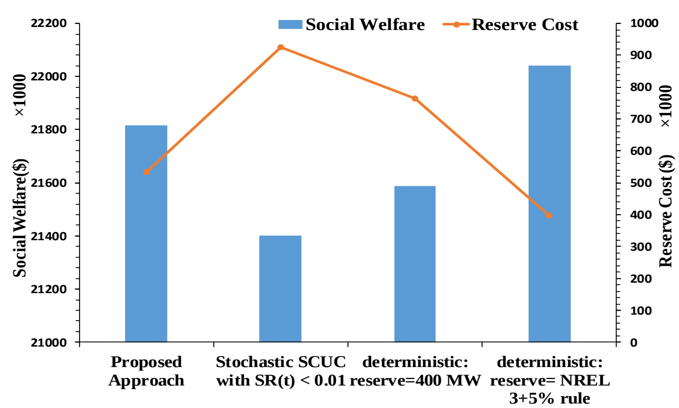

Fig. 3. Social welfare and reserve cost of the proposed approach and the benchmark settlements

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production of conventional generating units is adjusted in each scenario to satisfy all corresponding constraints associated with conventional generating units, transmission lines, and power balance. To compare the proposed risk-based model and the two-stage stochastic NCUC, we assign the reserve capacity of the first stage to maintain SR(t) below 1%.

The computation times in Cases 1, 2 and 4 are 82, 91 and 198 seconds respectively. In the two-stage stochastic NCUC approach, depending on the number of scenarios, the computation time would be considerably increased. For instance, if the number of scenarios is 5, 10, and 15, the computation time will be 423, 1169, and 3380 seconds, respectively. Hence, the proposed approach is much faster and efficient compared to the two-stage stochastic program.

In Fig. 2, the widely known strategies of setting the reserve capacity as the largest unit [41] (Case 1) and the deterministic policy of the NERL 3+5% rule [42] (Case 2) would result in an unacceptable level of system risk. Cases 1 and 2 show that using the deterministic approaches for risk-based scheduling with highly uncertain generation and demand cannot attain the optimal level of reserve. To maintain the system risk below the acceptable range, the SO in Case 3 commits a considerable reserve capacity to control the system risk. However, Case 3 is a costly approach to satisfy the system risk requirements which imposes the highest reserve cost and achieves the lowest social welfare in comparison to the other strategies. According to Figs. 2 and 3, the proposed risk-based NCUC approach in Case 4 can maintain the system risk within the acceptable range without dispatching an extensive level of reserve capacity. The unit commitment in Case 4 incurs the lower cost of reserve and achieve a higher social welfare in comparison to Case 3.

The deterministic NCUC approaches such as the ones studied in Cases 1 and 2 are inherently inefficient because the reserve capacity is determined without modeling the uncertain behavior of producers/consumers. In this regard, considering a deterministic reserve requirement will usually lead to either a low-cost high-risk operating strategy or a high-cost low-risk operating strategy [41]. For instance, the schedule devised by the strategy in Case 1 does not satisfy the required system risk level of 1% although it incurs lower reserve costs in comparison to Case 3. Likewise, by applying the NREL rule, the allocated quantity of reserve in Case 2 at each time interval is less than that in Case 1 (400 MW), which ends up with a higher system risk. Although the social welfare in Case 2 is higher due to the lower reserve cost, the system risk in Case 2 is also higher compared to that of the other Cases, which indicates the inefficiency of the deterministic policy.

The stochastic approach in the stochastic NCUC is also economically inefficient since highly uncertain Gencos and Discos are dispatched without considering their impact on the system security. In Case 3, the SO has to commit expensive reserve units to maintain the system security. In contrast to the conventional approaches described in first three Cases, the proposed approach considers both the price-quantity bids/offers and associated uncertainties in the NCUC process. Consequently, the energy will be traded with uncertain producers/consumers if and only if their offered prices outweigh the associated reserve costs incurred to the system by their uncertain behavior. On this basis, risky producers should submit lower energy prices to sell their produced energy and risky customers have to submit higher energy prices to satisfy their demand. This feature is thoroughly studied in the next subsection.

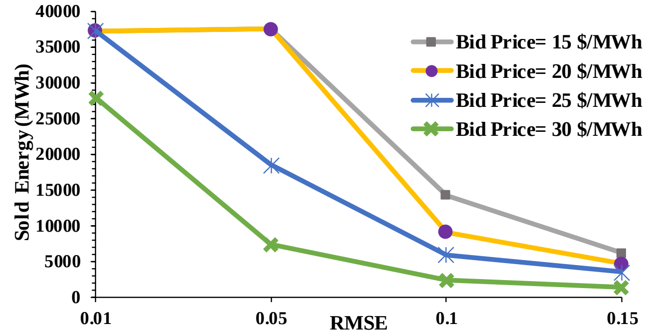

Fig. 4. Sold energy of P3 for different values of bid prices and RMSE.

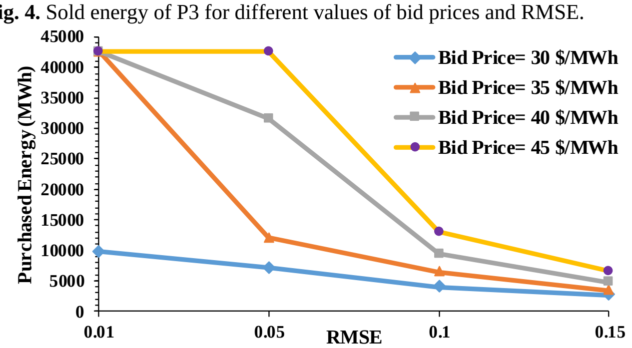

Fig. 5. Purchased energy of C3 for different values of bid prices and RMSE.

2) Revenue/Cost of Gencos/Discos

A salient feature of the proposed methodology is that the revenues/costs of Gencos/Discos not only depend on the submitted price-quantity bids but also are affected by the associated risk of the participants. On this basis, risky participants are automatically penalized for their risky behavior which incur reserve costs to the system. To highlight this feature, the accepted bids of typical producer P3 and consumer C3 in a day-ahead schedule are illustrated in Figs. 4 and 5 for different levels of RMSE. As demonstrated, the transacted energy by P3 and C3 in the market will be reduced as their associated RMSE aggravates. Consequently, a producer with high RMSE should offer lower offer prices to sell its produced energy. Similarly, by increasing the associated RMSE of a consumer, it should submit higher bid prices to purchase the required energy to supply its demand. On this basis, increasing the associated risk of market participants would reduce the revenues of producers and increase the costs of consumers.

Based on the above discussion, the associated reserve cost of each participant is incorporated in the proposed NCUC formulation. Accordingly, risky participants are automatically penalized by decreasing Gencos' selling prices and increasing Discos' purchasing prices. This penalty mechanism will incentivize stochastic producers/consumers to invest in risk reduction techniques such as implementing enhanced forecasting algorithms, installing storage facilities, using demand response, etc. to reduce their RMSEs and subsequently increase/decrease their revenue/cost.

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3) Effects of Correlations Among Market Participants

The other feature of the proposed NCUC lies in the fact that it can account for mutual correlations of different market participants. This is an important feature because the uncertainties of Gencos/Discos would have different impacts on power system operations. For instance, if associated uncertainties of a producer have positive correlation with the overall system demand, it can produce more energy when the system load increases which mitigates the generation shortages. Conversely, if a producer has negative correlation with the overall system demand, the generation capacity of the producer decreases when the overall system load increases which exacerbates the generation shortages. The following Cases are considered to study the effects of mutual correlations of Gencos/Discos on the social welfare, reserve costs and revenue/costs of Gencos/Discos, and the results are reported in Figs. 6, 7 and 8:

- Case 1: Consider the correlations of producers P1 and P2 and producers P4 and P5.
- Case 2: Consider the correlations of consumers C1 and C2.
- Case 3: Consider the correlations of consumer C1 and producer P2 and consumer C2 and producer P3.

In Case 1, the correlation of two different producers has been studied. Positive correlation of producers indicates that their production changes in the same direction. Thus, when producers have positive correlations, the system risk will increase which results in a higher reserve cost and a lower social welfare. In contrast, negative correlations of producers will alleviate the system risk as any increment in the output of one generating unit can be translated to a lower production of the other unit. Thus, negative correlation between producers would reduce the required reserves and lead to lower operation and reserve costs and a higher social welfare. Similar conclusions can be drawn for correlations of consumers as demonstrated in Case 2. In contrast to the first two Cases, the results in Case 3 shows that if the correlations of consumer and producer are positive, the total risk will be lower which will lower reserve costs and increase the social welfare. On the contrary, when the correlations of generation and demand are negative, the total risk will be higher.

As mentioned earlier, the proposed approach penalizes uncertain behavior of producers and customers as they incur reserve costs to the system. However, the proposed NCUC also favors producers that their uncertainties show negative correlations with other producers and positive correlations with consumers as they mitigate the overall system risks and enhance the social welfare.

For further clarification, the energy sold by producers in Case 3 are depicted in Fig. 8 using different values of correlation. As demonstrated here, by increasing the correlation of C1-P2 and C2-P3, a higher portion of bids submitted by these producers are accepted in the market which increases the amount of energy sold. Convesely, the SO decreases the purchased energy from other stochastic producers (P1, P4-P6) to balance the supply and demand. Accordingly, the proposed approach favors producers that their uncertain behavior can mitigate the overall system risk in power systems.

B. IEEE 300-bus test system

In order to demonstrate the efficiency and tractability of the proposed model in a larger scale system, we extend our study to the IEEE 300-bus test system which is composed of 300 buses, 69 generating units, and 411 transmission lines. The parameters of the system are obtained from MATPOWER [43]. We consider 10 generating units as stochastic producers with the total capacity of 1,058 MW. The details about the power profile and the submitted bid prices of stochastic producers are given in [40]. It is assumed that the producers are statistically independent with the same RMSE, and their submitted bid quantity is equal to their power profile. We implemented the proposed formulation on this test system to clear an hourly day-ahead market. The computation time, social welfare, and sold energy from stochastic producers as well as the reserve cost for different values of RMSE are reported in Table I.

From this table, it can be observed the computation time of all instances is less than 6 minutes, which shows the tractability of the proposed formulation for large scale systems. Meanwhile, it can be seen that with increasing the uncertainty of stochastic participants, the computation time would be higher. Another observation from this table is that social welfare will be reduced as the RMSE of stochastic producers aggravates due to reducing the sold energy from these producers. Please note that the submitted bid price of stochastic producers is considered less than that of conventional generating units. In contrast, the reserve cost does not have a monotonically trend, since it depends on both the amount of sold energy from stochastic producers and their RMSE.

TABLE I
COMPUTATIONAL RESULTS FOR THE IEEE 300-BUS SYSTEM

RMSE	Computation time (s)	Social welfare ($) $\times 10^5$	Sold energy from SP[1] ($)$\times 10^3$	Reserve Cost ($)$\times 10^3$
0.05	167	63154	11541	15041
0.1	217	63005	11083	28511
0.15	325	62972	466	0.793

1. Stochastic Producers

VI. DISCUSSIONS

A. Feasibility of the solution

In the proposed formulation, the required reserve capacity is determined assuming that the variability of R(t) is often limited to a small number multiplies by RMSE. Accordingly, in some scenarios, the required reserve capacity (R(t)) may exceed the committed reserve level. The power system risk defined in (15) demonstrates the probability that the actual reserve capacity exceeds its committed value.

Accordingly, the proposed approach is viewed to be similar to the chance-constrained optimization in which the solution might not be feasible in every possible scenario. However, similar to the chance constrained approach, the proposed approach ensures that the probability of satisfying the power balance constraints, quantified in (15), is above a certain level. Additionally, SO can increase the probability of satisfying the power balance constraints by adjusting the marginal factors α_{up} and α_{dn}. The calibration strategy for marginal factors is discussed in IV-B.

B. Calibration of Marginal factors α_{up}, α_{dn} and α_l

Marginal factors α_{up}, α_{dn} and α_l should be carefully selected to guarantee that the system risk and flow of transmission lines stay within the acceptable range. Since each power system is subject to different operating conditions (such as types of uncertainty sources, penetration of renewables, storage capacity etc.), the optimal values of these factors are system dependent. In this regard, the calibration process of α_{up}, α_{dn} and α_l is introduced here.

To calibrate α_{up} and α_{dn}, the historical data associated with the required system reserve (actually used to balance the supply and demand) has to be initially extracted. Then, the RMSE of the required system reserve can be calculated by incorporating the historical operational data in equation (5). Using (13)-(14), the up and down reserve capacities ($r^*_{up}(t)$ and $r^*_{dn}(t)$) can be assessed as a function of α_{up} and α_{dn}. The system risk $SR(t)$ over the historical data set can then be calculated for different values of α_{up} and α_{dn}. Now, α_{up} and α_{dn} should be calibrated so that the $SR(t)$ stays within the acceptable range over the historical data set. As a note, the calibration of α_l follows the same procedure. However, it will be more practical to consider equal α_l for transmission lines with similar conditions.

VII. Concluding Remarks

In this paper, the effects of variabilities in renewable power generation and load points is explored in NCUC solutions. To reach this goal, Individual and joint variabilities of exchanged energy in market environment are modeled using historical transaction data and applying the concept of RMSE. These models are then incorporated in formulation of the SCUS problem by which a stochastic model is extracted for this problem. The proposed NCUC model is then reformulated to apply SOCP for solving stochastic NCUC problem. In the case studies, the performance of the proposed NCUC model is compared against deterministic models and it was shown that this method can efficiently decrease the risk of system without extensive reserve requirements. The lower risk can be translated into higher social welfare. This is due to the fact that the proposed NCUC is modeled as a risk-based optimization and therefore the energy will be traded with uncertain producers/consumers if and only if their offered prices outweigh the associated reserve costs incurred to the system by their uncertain behavior. This salient feature not only guarantees the system with lowest risk scheduling strategies, but also it penalizes risky participants and motivates them to be equipped with risk reduction tools in power system operations. Finally, it has been discussed that how employing such a risk-based model for NCUC can lend the SO a hand in better understanding the effects of negative and positive correlation between producers and customers.

VIII. Acknowledgment

We would like to express our deep gratitude to Nobel prize winner professor Harry Markowitz whose outstanding works in the mean-variance model and Modern Portfolio Theory inspired us in writing this paper.

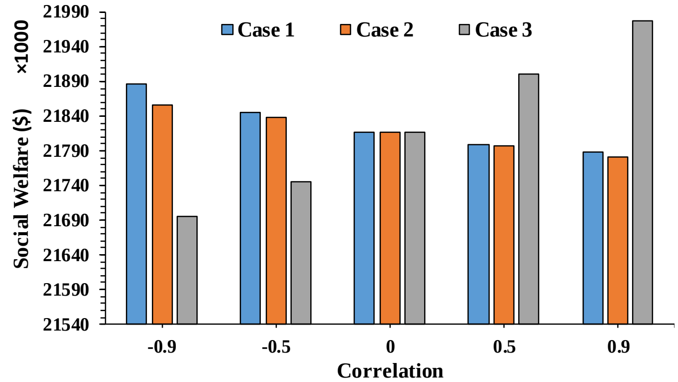

Fig. 6. Social welfare for different values of correlation.

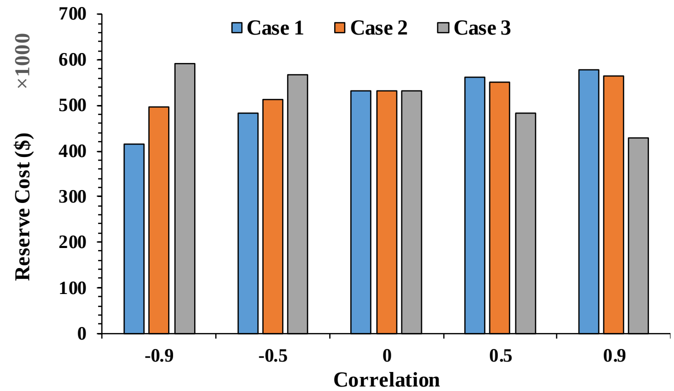

Fig. 7. Reserve cost for different values of correlation.

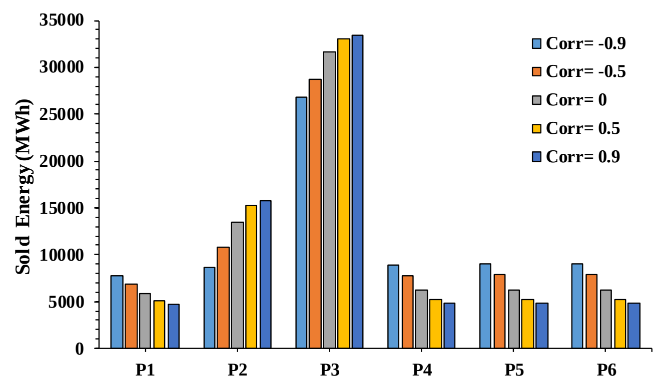

Fig. 8. Sold Energy by producers for different values of correlation (Case 3).

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