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Two-Stage Model for Security Network-Constrained Market Auction in Pool-Based Electricity Market

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Abstract – This paper presents a two-stage market auction model in a pool-based electricity market, which explicitly takes into account the system network security. The security network-constrained market auction model considers the use of corrective control to yield economically efficient actions in the post-contingency state, while ensuring a certain security level. Under this framework, the proposed model shows not only for quantifying the correlation between secure system operation and efficient market operation, but also for providing transparent information on the pricing system security for market participants. The two-stage market auction procedure is formulated using Benders decomposition (BD). In the first stage, the market participants bid in the market for maximizing their profit, and the independent system operator (ISO) clears the market based on social welfare maximization. System network constraints incorporating post-contingency control actions are described in the second stage of the market auction procedure. The market solutions, along with the BD, yield nodal spot prices (NSPs) and nodal congestion prices (NCPs) as byproducts of the proposed two-stage market auction model. Two benchmark systems are used to test and demonstrate the effectiveness of the proposed model.

Keywords: Available transfer capability, Benders decomposition, Market auction model, Nodal spot price, Nodal congestion price, Optimal power flow

1. Introduction

Electricity markets are continuously evolving, with the smart grid being the latest advancement in the modern electricity industry. Independent system operators (ISOs) are in charge of guaranteeing secure, stable, and reliable operation of the power grid within the context of a market operation environment [1]. Two typical challenges faced by the ISOs are the integration of security into the market-driven approach while preserving the effective market competitiveness, and the creation of market products to ensure the required system network security. Thus, pricing security becomes one of the most important aspects in electricity markets to address the correlation between the market and system operations. It is important, because it provides information that enables operation of the network under more secure conditions by appropriately responding to the given price signals. It can also help ISOs coordinate power transactions and aid the market participants in making profitable market decisions. The idea of pricing security was first introduced in [2], by means of representing system security through power flow constraints. In [3], the authors proposed a probabilistic method to obtain a social optimal level of security through simplified constraints, such as thermal limits in DC network. However, pricing security based on proper system constraints requires a variety of assumptions, owing to the complexity of accounting for accurate security network constraints in the market mechanism.

In general, the spot price mechanism is solved using an optimal power flow (OPF), which is a widely used market auction model in the electricity industry [4-6]. However, the power transfer limits in an OPF-based traditional market auction model are typically solved using the off-line studies. Incorporating system security through the application of these limits may not match the actual security levels, leading to insecure operating conditions and/or unnecessarily high spot prices related to an unrealistic modeling of system congestion. The technique proposed in [7] did not include the system network contingencies, which are critical issues in the proper representation of system network security. As the solution of the OPF problem needs an iterative process until a maximum security margin is obtained, a full-size iterative OPF may be computationally too demanding to be implemented in a short time frame, even if the contingency problem is considered. Consequently, traditional market auction schemes cannot provide sufficient security levels to find a more economical solution.

Security network-constrained approaches [8-15] for pricing in electricity markets are presented in more complex market auction models, in which the bids are matched to maximize social welfare while satisfying the specified security criteria. Unlike the OPF-based market auction model, it iterates between a base-case OPF problem

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and a set of predefined contingency system states. To guarantee the secure operation of power systems, two types of security controls are generally applied: preventive control and corrective control. Most of these approaches [16] consider the preventive controls, which impose additional constraints to enable a feasible operational condition in the post-contingencies; these controls do not actively change the control settings in the event of a contingency. Therefore the preventive controls are generally conservative and can be expensive owing to the high security network resulting cost from the over-tightened feasible region. Corrective controls, on the other hand, are usually employed to realize the post-contingency control actions for removing system violations. The corrective controls are, in fact, more appealing, because most market participants are reluctant to pay additional security network costs for a contingency that may not occur. It is obvious that the more economical, the system operation constraints implemented in the market mechanism process are, the more feasible the bid matching results will be, i.e., the available transfer capability (ATC) that results from this process will meet the system network constraints corresponding to the actual operating states related to the given security levels. In this vein, this paper is focused on corrective control, which unlike preventive control, represents the possibility of rescheduling control actions in post-contingency states.

This paper aims to propose a security network-constrained market auction model, which considers the use of economically efficient actions in the post-contingency state while achieving maximum social welfare. The model facilitates a reasonable tradeoff between security and economy in a day-ahead power pool trading. A two-stage market auction procedure is applied for solving the security network-constrained approach with Benders decomposition (BD), which efficiently solves and considerably speed-up the computations. This procedure is formulated as a primal-dual interior point method (PDIPM). This method has been proving to be robust, especially in large-scale power system, where the number of iterations increases slightly with the number of constraints and network size. It can be used in the BD where the original problem is decomposed into a master level and several slave levels, which are individually solved at each step and iteratively integrated, allowing parallel implementation in a distributed computing environment. Moreover, as a byproduct of the proposed model, economic signals given in the form of nodal spot prices (NSPs) and nodal congestion prices (NCPs) are ensured, based on a more accurate representation of system security, which is represented here through the "System-wide" ATC (SATC).

The remainder of this paper is organized as follows: Section 2 describes a two-stage formulation for the security network-constrained market auction model. Section 3 discusses the price mechanism for pool auction and presents detailed descriptions of each market and system solution by deriving BD based-two stage processes. In Section 4, the results of applying the proposed market auction model to two benchmark systems are presented and are discussed in detail. Finally, Section 5 summarizes the contributions of this paper and proposes possible future research directions.

2. Mathematical Formulation

2.1 Security network-constrained market auction model

The security network-constrained market auction for a pool-based electricity market can be modeled as follows [11]:

$$
\begin{aligned}
& Min\ S(x_0, u_0) \\
& s.t.\ G_0(x_0, u_0) = 0 \\
& H_0^{\min} \le H_0(x_0, u_0) \le H_0^{\max} \\
& G_p(x_p, u_p) = 0 \\
& H_p^{\min} \le H_p(x_p, u_p) \le H_p^{\max} \\
& \varphi(\bar{u}_0 - \bar{u}_p) \le \Theta \\
& p = 0, 1, 2, \cdots, N
\end{aligned} \tag{1}
$$

where S is the objective base-case function; x and u are the state (dependent) and control (independent) vectors, respectively; $p = 0$ is the base-case; and $p > 0$ represents the p^{th} post-contingency configuration. N is the number of contingencies considered. G_0 and H_{p} are the system equality and inequality, respectively, for the contingency case p; and $H^{\min}$ and $H^{\max}$ correspond to the lower and upper limits, respectively, of the inequality constraints. $\varphi(\bullet)$ is a Euclidean norm; $\bar{u}_0$ and $\bar{u}_p$ are subsets of u_0 and u_p, respectively; and Θ is the vector of the maximal allowed variations control variables reflecting corrective action.

The objective function in (1) is the social welfare maximization, i.e., the objective is to ensure that generator companies (GENCOs) maximize their incomes from power production, while energy supply companies (ESCOs) minimize the prices paid for their power demands. It is based on the bids submitted by the GENCOs and ESCOs and the system network data, and satisfies the operational and security related constraints. $\phi(\bar{u}_0 - \bar{u}_p) \le \Theta$, called the coupling constraint, implies that the rate of change in the control variables of the base-case is constrained by upper bounds. Detailed expressions of the objective function and the constraints used in the proposed model described in Appendix A.

The preventive control problems have a zero range in contrast to the corrective control problems whose non-zero regions reflect additional flexibility to address the onset of a contingency. The resulting security network cost may be increased greatly due to the over-restricted feasible range. Despite this desirable property, however, the corrective control problem is still quite difficult to solve because of the large number of nonlinear constraints and additional decision variables. Solving this problem directly for large-scale power systems with numerous contingencies would lead to prohibitive memory requirements. Therefore, an appropriate security network-constrained approach must be formulated by modeling the system and security network-constraints in detail while maximizing the social welfare.

2.2 Two-stage formulation

A large number of security network constraints incorporating post-contingency states make its solution onerous and even impossible because of both huge CPU-time requirement and convergence of the solution. In this regard, the security network-constrained approach shown in (1) is formulated by decomposing it into iterative two-stage market auction problem using BD [17]. The optimization problem is solved at the master level, while each contingency composes a slave level. A feasibility cut is derived and added to the master level. In the first stage, participants bid to the market for maximizing their profit, and the ISO clears the market based on social welfare maximization without considering the system network constraints. In the second stage, the ISO will consider the security network under the contingency condition, leading to a time intensive process. Mathematically, in (1), making $G_p(x_p, u_p)$ and $H_p(x_p, u_p)$ functions of u_p and not u_0 allows the complex security network-constrained OPF problem to be decomposed into N slave optimization levels, each of which minimizes $\left\| u_p - u_0 \right\|$ subject to the last three constraints in (1) that depend on u_p and x_p, and a master level that optimizes $S(x_0, u_0)$ subject to the first two constraints and the last constraint in (1) that depends on u_0. The master level is stated as

$$\begin{gathered} Min\ S(x_0, u_0) \\ s.t\ \ G_0(x_0, u_0) = 0 \\ H_0^{\min} \le H_0(x_0, u_0) \le H_0^{\max} \\ w(\overline{u}_0) \le 0 \end{gathered} \tag{2}$$

The last constraint in (2) is the feasibility cut which is a linear constraint that restricts the feasible region to enforce coordination of the solutions of the master level and the individual slave levels. The formulation of feasibility cuts can be described by

$$w^k(\overline{u}_0) = w_p^k + \lambda_p^k\left(\overline{u}_0 - \overline{u}_0^k\right) \le 0 \tag{3}$$

where w_p^k is the minimum value of the k-th iteration of the slave level for the p^{th} contingency; $\overline{u}_0$ is the subset of the base-case control vector obtained from the previous iteration; $\overline{u}_0^k$ is the subset of the base-case control vector for the k-th iteration, which is an information from the master level to the slave level p; and λ_p^k is the vector of dual variables for the k-th iteration, corresponding to the marginal increments in the objective value as $\overline{u}_0$ changed.

Obviously, the feasibility cut provides information about how the current $\overline{u}_0^k$ can be modified to reduce the problem infeasibility. The obtained schedules from the master level are passed to the slave levels to minimize the violations. The objective of the slave levels is to minimize the violations related to security network constraints. By adopting a penalty vector, the p^{th} contingency slave level can be formulated as follows:

$$\begin{aligned} & w_p = Min \sum_p \alpha_p \\ & s.t\ \ G_p(x_p, u_p) = 0 \\ & H_p^{\min} \le H_{\mathrm{p}}(x_p, u_p) \le H_{\mathrm{p}}^{\max} \\ & \phi(\overline{u}_0^k - \overline{u}_p) \le \Theta \\ & \alpha_p \ge 0 \\ & p = 1, 2, \cdots, N \end{aligned} \tag{4}$$

where α_p is a penalty vector that measures the incurred violations associated with the post-contingency control subset $\overline{u}_p$.

If the objective function w_p is equal to zero, a feasible solution $\overline{u}_p$ can be solved for the p^{th} slave level, which will not impose additional constraints on $\overline{u}_0^k$. On the other hand, if the objective function w_p is larger than zero, the p^{th} slave level solution will provide the master level with the amount of violations involved in the coupling constraints.

2.3 Two-stage solution procedure

The parallel processing technique using BD is implemented in a sequential manner. First, the master level is solved with the non-contingency market auction model without the last constraint of (2). Given the base-case $\overline{u}_0^0$ obtained by computing the initial master level, the slave levels are separately calculated to obtain a new base-case $\overline{u}_0^k$, and then the $\overline{u}_0^k$ from the different slave levels are simultaneously fed back to the master level, which is then solved according to (2) with all feasibility cuts considered. This creates a new base-case $\overline{u}_0^{k+1}$ and the slave levels are then computed, in parallel, under the new base-case $\overline{u}_0^{k+1}$ so that more accurate feasibility $w^k(\overline{u}_0)$ can be obtained for the master level based on the optimal results. The feasibility cuts return to the master level and the information is used to remove the infeasibility of the stressed slave levels. In practice, the value of the objective function $w^k(\overline{u}_0) = 0$ means that the system has sufficient margin and that this case is feasible. On the contrary, $w^k(\overline{u}_0) > 0$ implies that this case is infeasible with the current control variables. To ensure that this occurs, the two-stages the master level and slave levels are repeated until an optimum $\overline{u}_0^{k+1}$ is found, for which all w_p= 0, i.e., when the objective function w_p is equal to zero in all stressed slave levels, the optimal solution is determined.

3. Nodal Spot Price Mechanism of Pool Auction

3.1 Relationship between market structure and pricing mechanism

Market participants and ISOs depend on the market auction mechanism to set their bidding strategies during market business activity [18]. This paper considers a spot auction-based day-ahead energy market based on a pool in which market participants submit production and consumption bids to the ISO, which, in turn, clears the market using a proper market-clearing procedure. This process requires 24 hourly energy prices to be paid by consumers and charged by producers

Spot pricing represents reliable or crucial indicators and has good potential for providing economic signals for the overall system network operation [19]. Accurate knowledge of unbundled cost components is vital for pricing security correctly, especially for NSPs, which are mathematically calculated as the Lagrangian multipliers corresponding to the equality constraints in the security network-constrained approach. In this work, a NSPs structure is composed of two basic components as shown in Fig. 1. One is a generation marginal cost for supplying the next increment of electric power demand and transmission losses at a specific node. The other is the price for maintaining network security, termed as the NCPs, which directly indicates the severity of the congestion in the power system.

In an unconstrained market auction model, the NSP is the only price for a specific hour for the entire system network. However, when there is congestion, the bidding areas may exhibit different prices in the pool-based trading model [20]. The ISO should determine the minimal changes in the market results regarding submitting modified bid proposals for rescheduling power transactions while ensuring secure operation. Since higher NCPs reflect the presence of high degrees of congestion, it ultimately reduces social welfare and hinders the development of competitive power market. In this situation, the ISO must

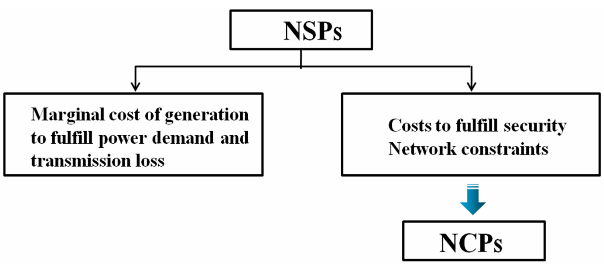


Fig. 1. Components of NSPs

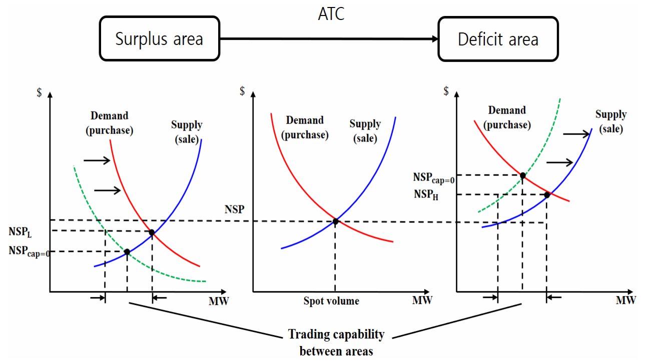


Fig. 2. NSP mechanism

take corrective control actions to maintain certain allowed system security levels, which usually result in increased prices for most market participants.

Additionally, available transfer capability (ATC) [11], which is defined as the maximum amount of energy that can flow from one bidding area to another, may vary, and thus, NSPs are obtained for each transmission-constrained area. An example of the supply and demand curves for two areas is shown in Fig. 2. Here, NSP_L and NSP_H represent the low and high prices during the full utilization of the ATC. NSP_{Cap}= 0 is a price in an area with an isolated price calculation. The ATC is included in the NSP mechanism by supply curve in Fig. 2, a lower price in the surplus area leads to greater purchases and fewer sales, which can provide a parallel shift in the demand curve. Whereas, by increasing the price in the deficit area, the market participants sell more and purchase less, and the sale can provide a parallel shift in the supply curve. The NSP mechanism is iterated so that the ATC between the areas is used to the maximum during every hour of operation to ensure that power transfer from the low-price area towards the high-price area. After that, the NSPs in the surplus and deficit areas are the new equilibrium points following the addition of power transfer between the areas of purchase and sale. The ISO determines the ATC for each hour of the day, and a volume corresponding to the transaction level on the constrained connection should be considered at a relatively low price in the surplus area (NSP_L) and a relatively high price in the deficit area (NSP_H).

3.2 Determination of optimum solutions

Most of the existing theories on NSPs use Lagrangian multipliers for the shadow prices, to evaluate the parameters or equivalent values of constraints for security and are based on the decomposition of the Lagrangian multipliers associated with the power flow equations into the sum of two terms as shown in Fig. 1. Then, there are two problems that must be solved: i) how to calculate NSPs and ii) how to decompose NSPs into congestion cost components. For constructing the decomposition model, PDIPM is implemented for solving the security network-constrained OPF problem [21]. The PDIPM has several advantages to be employed as a pricing tool. First, dual variables provide meaningful economic information because of their relations with shadow prices. Second, the price signals are more predictable and smoother according to the application of a logarithmic barrier function of slack variables as soft constraints.

By using slack variable vectors, (2) is transformed to make inequality constraints into equality ones as follows:

$$\begin{aligned} & Min\ S(z_0) \\ s.t.\ & G_0(z_0)=0 \\ & H(z_0)-s_L-H_{\min}=0 \\ & H(z_0)-s_U-H_{\max}=0 \\ & w(\bar{u}_0)+s_K\le 0 \\ & s_L\ge 0, s_U\ge 0, s_K\ge 0 \end{aligned} \tag{5}$$

where $z_0=[x_0\ \ u_0]^T$ are the primary nonnegative slack variables used to transform the inequality constraints to equalities.

After adding a logarithmic barrier function, the Lagrangian function of (5) incorporating all the constraints in the objective function can be formed as:

$$\begin{aligned} & L(z_0,s_L,s_U,\gamma,\pi_L,\pi_U,\pi_K,u) \\ & \quad = S(z_0)-\gamma^T G(z_0)-\pi_L^T(H(z_0)-s_L-H_{\min}) \\ & \quad -\pi_U^T(H(z_0)+s_U-H_{\max})-\pi_K^T w(\bar{u}_0) \\ & \quad -u(\sum_i \ln s_{\mathrm{L}i}+\sum_i \ln s_{Ui}+\sum_i \ln s_{Ki}) \end{aligned} \tag{6}$$

where γ^T, $\pi_L{}^T$, $\pi_U{}^T$, and $\pi_K{}^T$ are the Lagrange multi-plier vectors and μ is the barrier parameter. Basically, NSPs are the Lagrangian multipliers $\boldsymbol{\gamma}^{\mathbf{T}}$ associated with the power flow equation, and can be derived by applying the corresponding Karush–Kuhn–Tucker condition for Lagrangian functions as follows:

$$\begin{aligned} \gamma_{P_{S_i}} &= \left.\frac{\partial L}{\partial P_{S_i}}\right|_* \\ \gamma_{P_{Dj}} &= \left.\frac{\partial L}{\partial P_{D_j}}\right|_* \end{aligned} \tag{7}$$

where * denotes the optimal solution point. From (6)-(7), two extra expressions for NSPs are satisfied:

$$\begin{aligned} \mathrm{NSP}_{S_i} &= \boldsymbol{\gamma}_{P_{Si}} = \left.\frac{\partial C_{S_i}}{\partial P_{S_i}}\right|_* - \pi_{LP_{Si}} + \pi_{UP_{Si}} - \pi_{KP_{Si}}\left(\frac{w(\bar{u}_0)}{\partial P_{S_i}}\right) \\ \mathrm{NSP}_{D_j} &= \boldsymbol{\gamma}_{P_{D_j}} = \left.\frac{\partial C_{Dj}}{\partial P_{Dj}}\right|_* + \pi_{LP_{D_j}} - \pi_{UP_{D_j}} + \pi_{KP_{D_j}}\left(\frac{w(\bar{u}_0)}{\partial P_{D_j}}\right) \end{aligned} \tag{8}$$

Note that (8) includes terms that are dependent on the security network constraints under the N-1 contingency condition; therefore, (8) indicates how the system security affect NSPs. Using the decomposition formula for NSPs proposed in [22], (8) can be separated to obtain the NCPs, and then the equation for NCPs can be given by

$$\mathrm{NCP} = \left(\frac{\partial G^T}{\partial x}\right)^{-1}\frac{\partial H^T}{\partial x}(\pi_U-\pi_L) \tag{9}$$

Eq. (9) represents implicitly the dependence on security constraints throughout the system network, and is correlated to power transfer limits of transmission line and hence define prices associated with “System-wide” ATC (SATC), as a measure of the security margin of the current operating point. Generally, the ATC is a basic concept related to “area” interchange limits which are imposed by transmission rights. However, in this work this concept is extended to “system domain” [23], because of the increase in the complexity of the power transactions, which are not limited to within the “area domain”, but may occur anywhere in the whole power system. In this sense, it is expected that the SATC appropriately represents the system security for the pricing and congestion problem. The SATC is defined based on the loading parameter λ, as follows:

$$\mathrm{SATC}=\lambda T \tag{10}$$

where T represents the total transaction level of the system, which is defined as the actual power consumed by the loads, i.e. $T=\sum_{j\in J} P_{Lj}$.

In addition, the principle of “pay as NSPs” is required to settle the cost in the day-ahead energy markets in accordance with the participants’ contributions to the system network congestion and system losses. The total price paid to the ISO (Pay_{ISO}) is computed as the difference between the supply and demand payments as shown below:

$$Pay_{ISO} = \sum_{i\in I} C_{S_i}P_{G_i} - \sum_{j\in J} C_{D_j}P_{L_j} \tag{11}$$

4. Numerical Results

The security network-constrained market auction model for obtaining the market and system solutions was applied to two sample systems, one based on a 6-bus test system, and the second based on a 129-bus model of the Italian HV transmission system. These two differently sized test systems were used to compare the results of the proposed market auction model with the ones obtained from the OPF-based traditional market auction model [5]. Here, the power transfer limits needed in a traditional market auction model were obtained “off-line”, by means of a continuation power flow (CPF) technique [24]. An optimization package, the General Algebraic Modeling System (GAMS) [25] was employed in these case studies. During the test, the N-1 contingencies were considered as transmission outages only, and Θ were fixed to some constant, based on the corrective control capabilities of the suppliers and consumers as vectors with values equal to 10% and 15%, respectively which is given in the range of the decision variables of the maximum permissible control actions for each contingency. However, in practical power systems range of the decision variable for corrective control problem could be different from suppliers to suppliers or consumers to consumers.

4.1 6-Bus test system

Fig. 3 shows the 6-bus system representing three GENCOs and three ESCOs that provide the supply and demand bids, respectively. Table 1 represents supply and demand bids and the bus data for the market participants, whereas line data are illustrated in Table 2.

Table 3 shows the results for all buses obtained for the base operating state, which are used as the initial conditions for the master level. In the base-case solution, the total transaction level (TTL) is 282.8 MW. It is expected that the absence of security network constraints considering contingencies makes possible a high transaction level. Furthermore, NSPs and NCPs certainly have the uniform market solutions. When the security network-constrained approach is solved by the master-slave iteration using BD, the line 2-4 has the highest impact on the security of the system, so that the critical line 2-4 leads to the lowest SATC values.

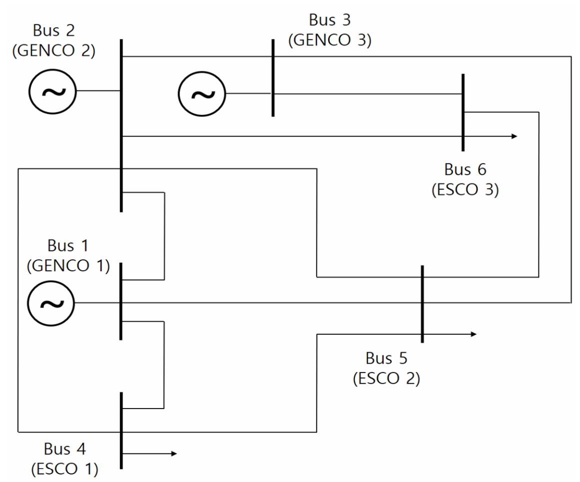


Fig. 3. 6-bus test system

Table 1. GENCO and ESCO bids and bus data for the 6-bus test system

Participant	C (\$/MWh)	P^{max} (MW)	P_{Lo} (MW)	Q_{Lo} (MVar)	P_{Go} (MW)	Q_G^{limit} (MVar)
GENCO 1	9.7	30	0	0	67.5	± 150
GENCO 2	8.8	37.5	0	0	103	± 150
GENCO 3	7.0	30	0	0	45	± 150
ESCO 1	12.0	37.5	67.5	45	0	0
ESCO 2	10.5	15	75	52.5	0	0
ESCO 3	9.5	30	67.5	45	0	0

Table 4 tabulates the optimal results by solving the proposed model. As can be seen, each bus is characterized by a different price, i.e. the market participants pay for their consumption or are paid for their production, based on their bids, as well as the congestions they cause in the network. It can be seen from Table 4 that ESCO 3 (Bus 3) has the highest NCP; hence, ESCO 3 needs to pay more for preserving the system secure than the other market participants, which is reasonable, because ESCO 3 has the most negative impact on the security of the system network.

For comparison between the traditional and proposed market auction models, Fig. 4 illustrates the NSPs and NCPs at each bus to study how the corresponding auction model affects the system and market conditions. Here, using the CPF, the power flow limits needed in the traditional model were obtained by means of off-line maximum loadability analysis when considering N-1 contingency criteria (line 2-4 outage). It can be observed the traditional model shows heterogeneous and higher NSPs and NCPs, indicating that the system network

Table 2. Line data for the 6-bus test system

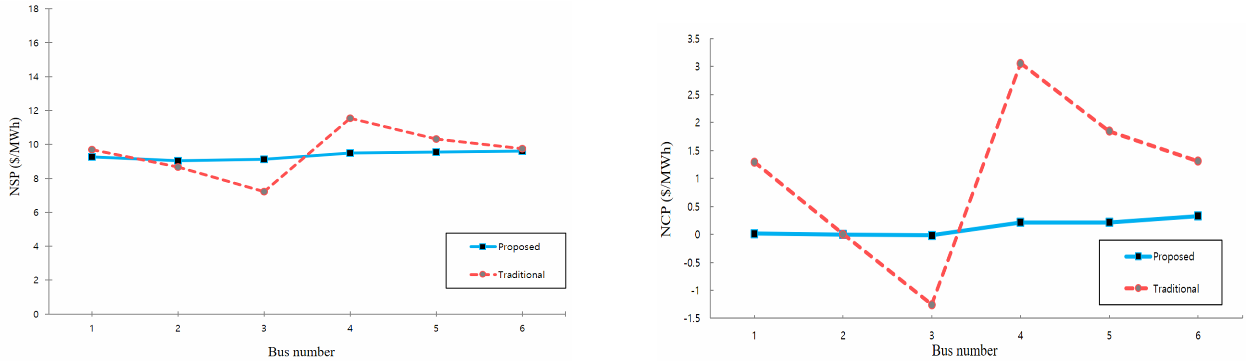
Line i-j	R_{ij} (p.u.)	X_{ij} (p.u.)	B_i / 2 (p.u.)	P^{max} (MW)	I^{max} (A)
1-2	0.1	0.2	0.02	11.7	200
1-4	0.05	0.2	0.02	39.8	200
1-5	0.08	0.3	0.03	50.4	200
2-3	0.05	0.25	0.03	18.3	200
2-4	0.05	0.1	0.01	57.7	200
2-5	0.1	0.3	0.02	33.1	200
2-6	0.07	0.2	0.025	43.3	200
3-5	0.12	0.26	0.025	23.0	200
3-6	0.02	0.1	0.01	47.5	200
4-5	0.2	0.4	0.04	7.7	200
5-6	0.1	0.3	0.03	2.2	200

Table 3. Base-case solutions in 6-bus test system

Participant	NSP (\$/MWh)	NCP (\$/MWh)	P_S (MW)	P_D (MW)	P_0 (MW)
GENCO 1	9.02	0.024	30.00		67.5
GENCO 2	8.97	0.000	37.50		103.0
GENCO 3	9.11	-0.011	9.68		45.0
ESCO 1	9.45	0.145	-	37.50	67.5
ESCO 2	9.56	0.183	-	15.00	75.0
ESCO 3	9.41	0.121	-	20.33	67.5

Table 4. Results of proposed market auction model in 6-bus test system

Participant	NSP (\$/MWh)	NCP (\$/MWh)	P_S (MW)	P_D (MW)	P_0 (MW)	*Pay* (\$/h)
GENCO 1	9.27	0.013	28.26	-	67.5	-887.7
GENCO 2	9.04	0.000	34.26	-	103.0	-1,240.8
GENCO 3	9.13	-0.016	9.40	-	45.0	-496.7
ESCO 1	9.51	0.217	-	36.01	67.5	984.4
ESCO 2	9.55	0.214	-	15.00	75.0	859.5
ESCO 3	9.62	0.328	-	19.51	67.5	837.0



(a) NSPs (b) NCPs

Fig. 4. Comparison of NSPs and NCPs in 129-bus system model

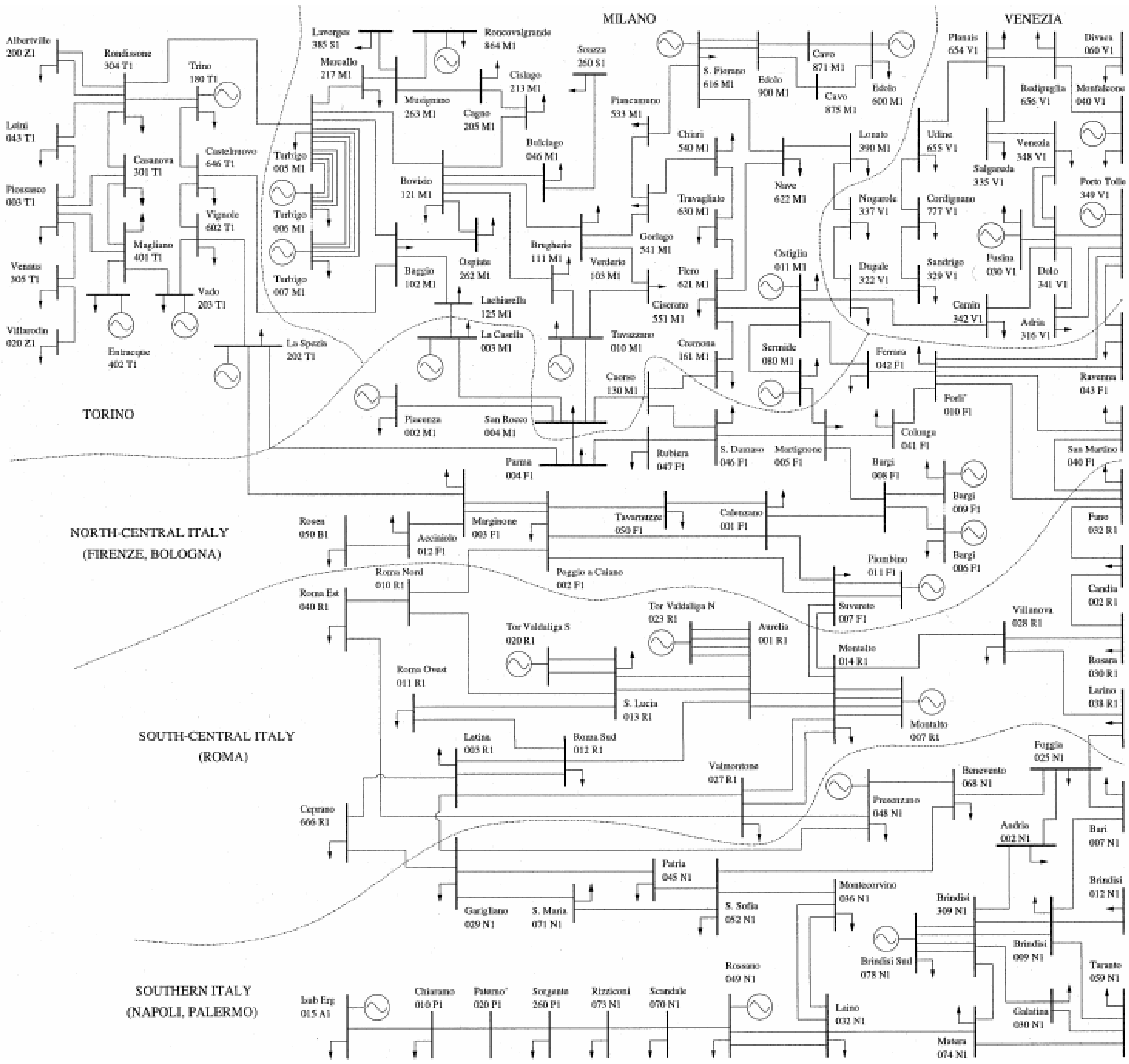


Fig. 5. 129-bus system model

constraints negatively influence the market solutions. On the other hand, the market solutions of the proposed model provide more homogeneous NSPs and lower NCPs. When the post-contingency corrective control actions are applied, the NCPs may increase initially; however the proposed model encourages the consumers to reduce their demands which in turn, gradually enhance the system network security, adjusting the NCPs to lower values. Thus, the

Table 5. Comparison of system network solutions in 6-bus test system

Market auction model	TTL (MW)	SATC (MW)	TSL (MW)	Pay_{ISO} ($/h)
Traditional	231.7	0.8	5.57	385.7
Proposed	280.5	30.3	10.15	55.7

NSPs and NCPs at a given bus obtained using the proposed model have a better profile than those obtained using the traditional and model.

Table 5 shows the resultant system network solutions for the traditional and proposed models. The security network-constrained approach provides higher TTL and SATC values than the OPF-based traditional approach, which is computed off-line indicating that these power transfer limits are not adequate constraints for representing the actual system congestion. In the end, the improved NSPs result in a lower PayISO, i.e., the NCPs are lower, even though the total system losses (TSL) are higher, which is to be expected, as the TTL is higher. These results demonstrate that the proposed model yields better market and system conditions than the traditional model, while meeting the required security constraints. Certainly, the more accurate the system operation constraints considered in the market clearing process are, the more feasible the bid matching results will be, i.e., the power transactions that result from this process will meet system security constraints corresponding to the actual operating conditions. Therefore, the proposed auction model guides the market participants towards optimum operating conditions satisfying both economy and security measures in pool based-electricity markets.

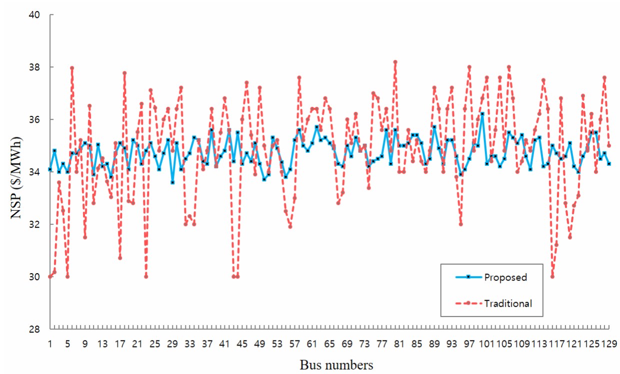
4.2 129-bus system

The 129-bus model of the HV Italian system is implemented using the proposed market auction model for realistically sized power networks as illustrated in Fig. 5. In this model, 32 suppliers and 82 consumers are assumed to participate in the market auction, and the system data and market data can be found in [19]. At the beginning, the market solution for the base operating state is computed in (2) without including the security network constraints under the N-1 contingency condition, and then the TTL is determined to be 26,865MW. When the security network-constrained approach is calculated by the master-slave levels using BD, the outage of the line connecting Bus 36 (Baggio) to Bus 50 (Turbigo) of the Milano area will be the most critical, because it has the lowest SATC. Table 6 shows the market solutions for some of the significant participants when the Italian 129-bus system is subdivided geographically.

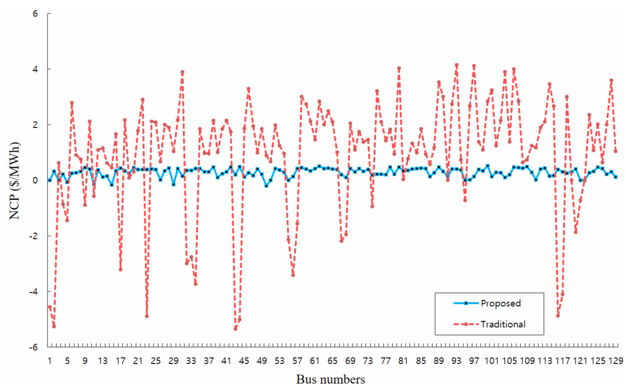
Fig. 6 shows a comparison of the NSPs and NCPs obtained with the traditional and proposed models; this shows a behavior similar to that of the 6-bus test system, confirming that an appropriate representation of security

Table 6. Results of proposed market auction model in 129-bus system

Bus	Participant	NSP ($/MWh)	NCP ($/MWh)	P_S (MW)	P_D (MW)	P_0 (MW)	*Pay* ($/h)
1	Entracque	34.1	0.0035	348	-	488	-28,508
3	Trino	34.0	0.0013	263	-	266	-17,986
10	Piacenza	35.2	0.4342	173	-	201	-13,165
15	Portotolle	33.8	-0.1754	398	-	1,297	-57,291
34	Villarodin	35.3	0.4250	185	-	614	-28,205
50	Turbigo	33.7	-0.2117	521	-	264	-26,455
120	Lavorges	35.1	0.4001	309	-	531	-29,484
26	Casanova	34.2	0.0921	-	74	350	14,501
62	Parma	35.7	0.5101	-	121	412	19,028
70	Roma N.	34.6	0.3041	-	133	500	21,902
88	Galatina	34.5	0.2743	-	66	213	9,626
105	Colunga	34.5	0.2009	-	125	310	15,008
110	Rubiera	34.6	0.2886	-	98	323	14,567
122	Cagno	34.0	0.0043	-	59	189	8,432



(a) NSPs



(b) NCPs

Fig. 6. Comparison of NSPs and NCPs in 129-bus system model

network-constraints will certainly result in a better distribution of results with reduced impacts on the system congestion and electricity prices. The NSPs are higher for the traditional model than those obtained with the proposed model, as the system is more congested. That is, this comparison shows that the security network-constrained approach provides lower and more uniform NSPs and NCPs than the OPF-based traditional approach. The proposed model yields a higher TTL, while reducing the

Table 7. Comparison of system network solutions in 129-bus system

Market auction model	TTL (MW)	SATC (MW)	TSL (MW)	Pay_{ISO} (\$/h)
Traditional	20,045	291	91.8	19,986
Proposed	24,105	2,838	161.7	6,236

Table 8. Simulation durations in two test system

Case	Traditional market auction model	Proposed market auction model
6-bus	9.967 sec	6.645 sec
129-bus	21.15 min	1.33 min

Pay_{ISO}, as illustrated in Table 7. Note that the rescheduling of the demand bids also result in slightly lower NSPs and NCPs, as a consequence of including more precise security constraints, which in turn results in a lower Pay_{ISO} value with respect to that paid with the traditional model. This, in turn, gradually improves the system security, resulting in a decrease in the TSL. In other words, through the post-contingency control strategy, it should be pointed out that a corrective control strategy is more economical, given that there is a small but non-zero correction time available for implementing post-contingency changes to the control variables. The behavior of market participants can be gradually adjusted such that to have less expensive NSPs while operating the system within reasonable security margins. Accordingly, the proposed market auction model provides guidelines for the market participants toward optimum operating conditions satisfying both economy and security measures in the day-ahead power pool trading. Therefore, this approach can be regarded as transparent with fair market interventions.

4.3 Computational performance and contribution

Since the solution of traditional OPF based-market auction model requires an iterative procedure till a maximum security margin is gained, such a full size iterative optimization problem should be regarded too lengthy in a short-term time frame. For computing the efficiency in the proposed market auction model, the determination of the security network constraints and the *N*-1 contingency is essentially decoupled using the BD. The key feature of this paper is the focus on how to add the feasibility cut to the master level is still an important issue because it affects the convergence and computational burden of the master-slave iteration process. In general, two different solution schemes, called serial and parallel methods can be used to add the feasibility cut to the master level. The serial method may largely decrease the complexity of the master level, but unfortunately it requires massive calculation time of the master-slave iteration process. Sometimes, it could make the BD fail or produce a sequence that don't converge either to a local or global optimum. On the other hand, the parallel method is to add all the formed the feasibility cuts to the master level simultaneously. Here, all the slave levels associated with security network constraints in different *N*-1 contingencies are processed in parallel. Compared with the serial method, this method guarantees the convergence about the oscillation of the master-slave iteration process.

The CPU-times taken by the traditional and proposed market auction models for the two test systems are compared in Table 8. In the 6-bus system, the traditional model took 9.967 s, whereas the proposed model took 6.645 s. In the 129-bus system model, the traditional model requires approximately 21.15 min whereas the proposed model requires approximately 1.33 min. According to the use of parallel method of BD, a small number of iterations are usually needed; hence, the CPU times of the proposed model are obviously faster than those of the traditional model. Actually, given the parallel processing nature of BD, these results show that the computation speed can be increased for large-scale power system that readily fits with the requirements of realistic day-ahead power pool trading. Finally, the main contribution of this paper is summarized as follows.

The proposed market auction model can improve the economic signals of pool-based energy market since the appropriate corrective control actions are effectively applied. Thus, the OPF framework in this paper not only retains advantages of the security network-constrained market auction model in capturing the efficient solutions but also provides transparent information on the pricing system security for market participants.

One of the main advantages of the proposed model is the fact that economic efficiency in the form of NSPs and nodal NCPs are ensured, based on accurate evaluation of the SATC for a whole system, as a measure of the security margin of the current operating point. With this aim, power transfer limits are not computed off-line, which is the current common strategy, but are properly represented in on-line market computations by means of the inclusion of a loading parameter in the system network constraints.

Another advantage of the proposed two-stage market auction model is that commercial mathematical programming languages and solvers can be used to formulate it, making it more practical and easier to implement. In the BD, the slave levels are solved independently of each other, and then the convergence in master-slave iteration process can benefit directly from parallel method. Owing to such computational efficiency, two-stage procedure is able to solve for large-scale problems, therefore this allows to test the practical feasibility of the proposed model using larger and more realistic test systems.

5. Conclusion

Optimal nodal pricing is a major concern for market participants, in addition to being a multifunctional task for the ISOs. In the pool-based electricity market, this paper proposed a two-stage procedure for a security network-constrained market auction model incorporating post-contingency remedial actions. To increase the overall computation efficiency via parallel processing, the determination of the security network constraints and the N-1 contingency was essentially decoupled from the proposed approach using BD, and optimal pricing expressions were derived simultaneously by computing NSPs and NCPs with respect to ensuring security level. The feasibility and effectiveness of the proposed market auction model was tested on a simple system as well as on a realistic network. The result obtained, when compared to those obtained via a traditional market auction model, showed that the proposed model offered better market solutions based on a more accurate representation of the system security, which is represented here through the SATC. Certainly, the propose model is clear enough for all market participants and captures the efficient solution transparently. Further research work will concentrate in extending the proposed two-stage market auction procedure to multi-stochastic framework.

Appendix A

Explicit representation of system network-constrained market auction model

$$Min\ S = -\left(\sum_{j \in J} C_{D_j}(P_{D_j}) - \sum_{i \in I} C_{S_i}(P_{S_i}) \right) \tag{A.1}$$

$$s.t.\ G_p(x_p, u_p) = G_p(V^p, \theta^p, K_G, P_S^p, P_D^p) = 0 \tag{A.2}$$

$$P_{Si}^{\min} \le P_{Si}^p \le P_{Si}^{\max} \qquad \forall i \in I \tag{A.3}$$

$$P_{Dj}^{\min} \le P_{Dj}^p \le P_{Dj}^{\max} \qquad \forall j \in J \tag{A.4}$$

$$Q_{Gi}^{\min} \le Q_{Gi}^p \le Q_{Gi}^{\max} \qquad \forall i \in I \tag{A.5}$$

$$\left| I_{ij}^p \right| \le I_{ij}^{\max} \qquad \forall (ij) \in L \tag{A.6}$$

$$\left| P_{ij}^p \right| \le P_{ij}^{\max} \qquad \forall (ij) \in L \tag{A.7}$$

$$V_k^{\min} \le V_k^p \le V_k^{\max} \qquad \forall k \in B \tag{A.8}$$

$$\left\| P_s(u_0) - P_s^p(u_p) \right\| \le \Delta P_s^p \tag{A.9}$$

$$\left\| P_d(u_0) - P_d^p(u_p) \right\| \le \Delta P_d^p \tag{A.10}$$

and

$$P_G^p = (1 + \lambda + K_G) P_G \tag{A.11}$$

$$P_L^p = (1 + \lambda) P_L \tag{A.12}$$

$$P_G = P_{G0} + P_{SG} \tag{A.13}$$

$$P_L = P_{L0} + P_{DG} \tag{A.14}$$

$$Q_L = P_L \tan(\phi_L) \tag{A.15}$$

where C_{Dj} is the demand bid of unit j in \$/MWh; C_{Si} is the supply bid of unit i in \$/MWh; P_{Dj} is the demand bid volume of unit j in MW; and P_{Si} is the supply bid volume of unit i in MW; I and J are the sets of the generator's units and power consumer's blocks, respectively; V and θ are the bus voltage magnitude and angle, respectively, while K_G is a scalar variable used to account for the system losses by means of either a unique or distributed slack bus; P_{Si}^{min} and P_{Si}^{max} are the lower and upper limits, respectively, of the supply bid volume of unit i in MW; P_{Dj}^{min} and P_{Dj}^{max} are the lower and upper limits, respectively, of the demand bid volume of unit j in MW; Q_{Gi}^{min} and Q_{Gi}^{max} are the lower and upper limits of reactive power limit at unit i in MVAR; I_{ij} is the line current between the nodes i and j; I_{ij}^{max} is the upper limit of line current between nodes i and j, and L is the set of indices of the transmission lines; P_{ij} is the real power flow transferred from bus i to bus j; P_{ij}^{max} is the upper limit of real power flow between bus i and bus j; V_k^{min} and V_k^{max} are the lower and upper limits, respectively, of the voltage magnitude at node k; B is the set of indices of the network buses; P_s is the base-case vector of the real power injected; P_s^p is the corrective vector of the real power injected for the p^{th} configuration and ΔP_s^p is the vector of corrective control capabilities of the suppliers; P_d is the base-case vector of the real power withdrawn; P_d^p is the corrective vector of the real power withdrawn for the p^{th} configuration, and ΔP_d^p is the vector of corrective control capabilities of the suppliers; P_d is the base-case vector of the real power withdrawn; P_d^p is the corrective vector of the real power withdrawn for the p^{th} configuration, and ΔP_d^p is the vector of corrective control capabilities of the consumers; P_{G0} and P_{L0} are the generator and load powers, respectively, which are not part of the market bidding and λ is the loading parameter that drives the system to its maximum loading condition.

Eq. (A.1), the objective function, represents the social welfare, and it has two parts. The first part consists of the sum of the accepted demand bids (P_{Dj}) times their corresponding bid prices (C_{Dj}) in \$/MWh, and the second part is the sum of the accepted production bids (P_{Si}) times their corresponding bid prices (C_{Si}) in \$/MWh. Constraint (A.2) is the standard power flow equation. The state vector x_p includes V, θ and K_G for the p^{th} configuration, while the control vector u_p includes P_S and P_D for the p^{th} configuration. In this work, a distributed slack bus technique is used for solving the proposed market auction problem because it allows a fair and reasonable distribution of the transmission losses among all market suppliers. Constraints (A.3) and (A.4) are the supply and demand bid blocks, respectively. Constraint (A.5) relates the reactive powers of generators for security loading conditions. Constraint (A.6) establishes bounds on the actual thermal magnitudes of the transmission line, while Constraint (A.7) enforce bounds on power transfer, based on the N-1 contingency criterion. Constraint (A.8) establish bounds on voltage magnitudes for security loading conditions

Constraints (A.9) and (A.10) represent post-contingency control actions for the suppliers and consumers, respectively. Constraints (A.11)-(A.14) relate generator and load powers for the p^{th} configuration. Here, it is assumed that the constraints (A.11) and (A.12) have a solution for $\lambda=0$, i.e., the base loading does not exceed the maximum system loading. Finally, constraint (A.15) relates the reactive and active power demands with constant power factor.

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