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The Effects of Spinning Reserve Uncertainty and Demand Response Programs on Transmission-Constrained Bidding Strategy

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ABSTRACT: In the electricity market, generation company attempts to maximize their profit in a bidding strategy approach. As the transactions of power and spinning reserve are done in a transmission network, consideration of transmission constraints and spinning reserve uncertainties becomes necessary. In the bidding strategy problem, there are various demand uncertainties. Usually, electricity markets consider a fixed spinning reserve with fixed request probability to ensure that demand is met. However, the actual spinning reserve is stochastic in quantity and requests hours that should be modeled and simulated. Another demand uncertainty is demand response programs include various stochastic types. One of the most famous demand response programs is electric vehicle parking with stochastic charging/discharging amounts and hours. The objection of this study is solving the bidding strategy problem considering transmission constraints, spinning reserve uncertainty, and electric vehicle parking as a demand response program based on a heuristic approach. An actual spinning reserve model using normal distribution is proposed and three case studies are presented. In the first case, improvement in profit of the generation company by 4.15-47.95% and 20.84-31.30% under single and double-sided auctions are reached, respectively. Where transmission constraints and spinning reserve uncertainty are considered, the optimal bidding strategy problem is solved in the energy and spinning reserve market for three-generation companies in the IEEE 6-bus network where transmission constraints are satisfied at all scenarios of spinning reserve requests. When electric vehicle parking is considered, it is shown that demand response programs have direct effects of bidding parameters such as market clearing price, generation companies power awarded and profits.

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1- Introduction

In an electricity market for energy and spinning reserves, generation companies (GENCOs) attempt to maximize their profits by competing with other opponents [1]. Usually, GENCOs participate in a transmission network and therefore, transmission constraints should be considered in the bidding strategy problem.

For market participants, it is very important to know forecasted hourly demand that is naturally uncertain due to unwanted hourly increases/decreases and should be considered in bidding strategy problems. Usually, a fixed spinning reserve is considered equal to a certain percent of demand. However, that is not an actual model, and spinning reserve uncertainty in quantity and request probability should be studied.

The demand may be uncertain in another form that is demand response (DR) programs when demand is changed or shifted suddenly or with scheduling. One of the most important types of DR is electric vehicle (EV) parking. The EV parking benefits from charging/discharging EVs and therefore a huge demand uncertainty is forced to market.

There are studies on bidding strategy problems under transmission networks considering DR, as summarized in Table 1 and outlined next.

1- 1- Literature review

The bidding strategy for energy and spinning reserve markets is solved in [1] when evolutionary programming (EP) and sequential quadratic programming (SQP) are used without spinning reserve uncertainty, DR, and transmission constraints.

A genetic algorithm (GA) is used to solve the bidding strategy problem in [2] without considerations for transmission constraints and DR programs.

Optimal bidding strategy with considerations for market power and transmission constraints is examined based on GA by Badri [3, 4]. In that study, the impacts of the energy market clearing process on GENCOs characteristic and final marginal cost price (*MCP*) are discussed.

Li and Shahidehpour solved a transmission-constrained bidding strategy [5] where DR programs and spinning reserve

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Table 1. Summary of studies on optimal bidding strategy problem in the literature.

Ref.	Market participation		Consideration			
	Energy	Spinning reserve	Transmission constrainers	Spinning reserve uncertainty	DR	EV parking
[1]	●	●				
[2]	●	●				
[3]	●		●	●		
[4]	●		●	●		
[5]	●		●	●		
[6]	●		●	●		
[7]	●		●	●		
[8]	●		●	●		
[9]	●		●	●		
[10]	●		●	●		
[11]	●	●				
[12]	●	●	●	●		
[13]	●		●	●		
[14]	●		●	●		
[15]	●	●	●	●		
[16]	●		●	●		
[17]	●		●	●		
[18]	●		●	●		
[19]	●	●				
[20]	●	●				
[21]	●				●	
[22]	●				●	
[23]	●				●	
[24]	●				●	●
[25]	●				●	
[26]	●				●	
[27]	●				●	
[28]	●				●	
[29]	●				●	
[30]	●				●	
[31]	●				●	
[32]	●				●	
[33]	●	●				
[34]	●	●			●	
[35]	●					
[36]	●	●				
[37]	●	●		●		
[38]	●					●
[39]	●				●	
[40]	●					●
This study Case (a)	●	●	●			
This study Case (b)	●	●	●	●		
This study Case (c)	●	●			●	●

uncertainty are not considered.

Bidding strategy of thermal generation units (TGUs) is solved for the six-bus network [6], IEEE 39-bus network [7], and IEEE thirty-bus network [8]. Similar studies are presented by Kardakos et al. [9, 10] using GAMS.

Nazari and Ardehali [11] have solved the bidding strategy for the coordinated power system in day-ahead energy and spinning reserve markets considering wind uncertainty and pollution emission. However, transmission constraints and spinning reserve uncertainties are not considered.

Zolfaghari Moghaddam and Akbari [12] have presented a bidding strategy for several price-taker plug-in electric vehicle aggregators.

A stochastic bi-level bidding strategy is proposed by

Rayati et al. [13] for integrated wind and gas turbines in the real-time market. The bidding strategy is formulated by Liu et al. [14] for microgrids and the Nash Equilibrium of the market is achieved.

Distributed energy resources aggregators bidding strategy in a non-cooperative electricity market has been developed by Li et al. [15]. However, spinning reserve uncertainties are not considered.

Moiseeva and Hesamzadeh [16] have proposed a stochastic bi-level program for the bidding strategy problem of hydropower. A self-generation scheduling method for power GENCOs with renewable generation units has been presented by Renani et al. [17].

Karimi et al. [18] have made use of a model to involve the GENCOs in transmission investment through a joint venture agreement. However, spinning reserve uncertainties are not considered.

The optimal bidding strategy problem for GENCOs in energy and spinning reserve markets is examined by Nazari and Ardehali [19, 20]. However, transmission constraints and spinning reserve uncertainties are not considered.

It is noted that in the above papers [1-20], DR programs are not considered. Next, a literature review of references about bidding strategy considering DR is done.

In [21], the bidding and purchasing strategy simultaneously employing the smart meter data and functions are determined. However, EV parking, spinning reserve uncertainty, and transmission constraints are not considered.

Reference [22] presents a mathematical model for the energy bidding problem of a virtual power plant participating in the electricity and DR markets without considerations for EV parking, spinning reserve uncertainty, and transmission constraints.

The bidding strategy for the aggregator considering the bottom-up responsiveness of residential customers is solved in [23].

Operation models of multiple virtual power plants under bidding strategy problem is examined in [24]. However, EV parking, spinning reserve uncertainty, and transmission constraints are not considered.

Day-ahead market bidding strategy for load aggregators engaging DR is presented in [25] without considerations for EV parking, spinning reserve uncertainty, and transmission constraints.

Reference [26] proposes an approach to solve the bidding strategy of DR aggregators. However, EV parking, spinning reserve uncertainty, and transmission constraints are not considered.

The optimal bidding strategy of electricity retailers considering time-of-use rate DR programs under market price uncertainties is presented in [27] without considerations for EV parking, spinning reserve uncertainty, and transmission constraints.

The market bidding strategy of the microgrids considering DR and energy storage potential flexibilities is studied in [28]. However, EV parking, spinning reserve uncertainty, and transmission constraints are not considered.

Reference [29] proposes a novel scheme for optimizing the operation and bidding strategy of virtual power plants without considerations for EV parking, spinning reserve uncertainty, and transmission constraints.

A comprehensive stochastic decision-making model for the coordinated operation of wind power producers and DR aggregators participating in the day-ahead market is done in [30] without considerations for EV parking, spinning reserve uncertainty, and transmission constraints.

In [31], the authors focus on determining the optimal bidding strategy in the day-ahead energy and spinning reserve markets for an aluminum smelter. However, EV parking, spinning reserve uncertainty, and transmission constraints are not considered.

Ref. [32] contributes a strategic bidding model for planning with short-term energy storage while considering the uncertainty of consumer DR and load response programs, simultaneously.

Ref. [33] formulates the operation mechanism and a day-ahead robust bidding model for a virtual power plant in the peak-regulation market. Case studies reveal that the mechanism can integrate various resources of electricity, cooling energy, thermal energy, and natural gas in energy demand and supply sides to participate in the peak-regulation market and improve the economy of the system.

A convex bidding model is formulated in [34] for wind, pumped storage, and DR in both day-ahead energy and ancillary service markets by considering upward spinning reserve and downward spinning reserve. Also, fixed, shiftable, curtailable, and incremental loads are considered for DR.

The main goal of [35] and [36] is to propose a novel multi-objective bidding strategy framework for a wind-thermal-photovoltaic system in the deregulated electricity market for the first time.

In Ref. [37], strategic bidding of an energy storage agent in a joint energy and reserve market under stochastic generation is solved.

Aiming at the problem of insufficient research on the interactions of various participants in the energy and frequency regulation market that takes into account the participation of wind power and large-scale EV, a bidding strategy for wind power and large-scale EVs in the day-ahead energy market is proposed in [38].

In [39], the bidding and purchasing strategy simultaneously employing the smart meter data and functions are determined. A two-agent deep deterministic policy gradient method is developed to optimize the decisions through learning historical bidding experiences.

Ref. [40] concentrates on the optimal bidding strategy of a plug-in EV aggregator using indirect load control in the day-ahead energy market, which is generally formulated as bi-level programming.

As shown in Table 1, the studies that consider spinning reserve in the optimal bidding strategy problem with considerations for transmission constraints are limited and the probability of spinning reserve request is assumed to be fixed throughout the day in the day-ahead electricity markets.

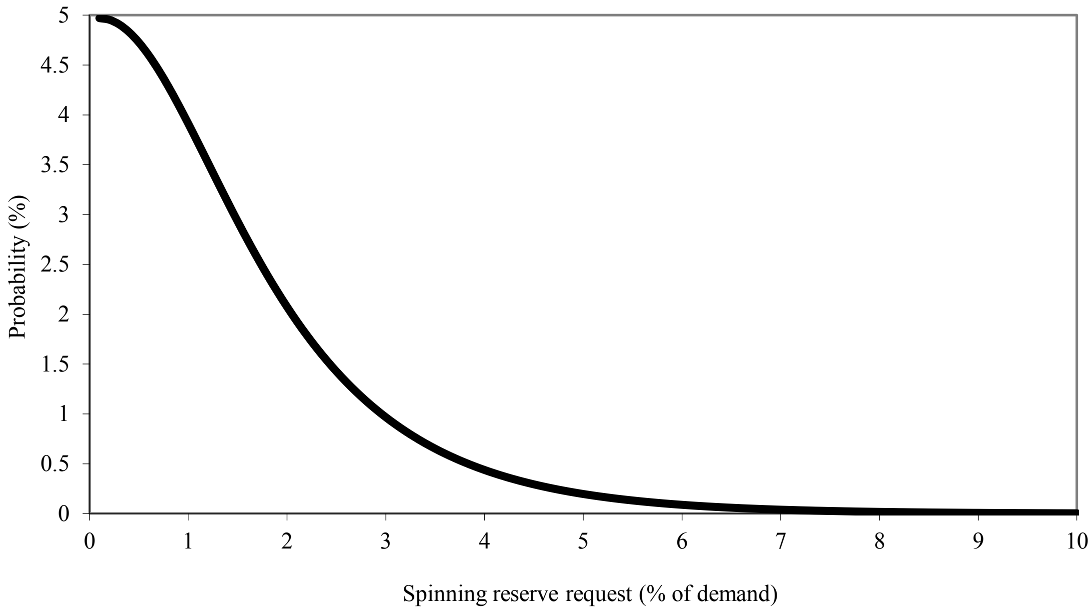


Fig. 1. Normal distribution of spinning reserve request probability

However, in competitive electricity markets, the probability associated with the spinning reserve and the spinning reserve request is variable due to the volatile market prices and demand uncertainty [41]. Also, consideration for different types of DR programs is necessary because of their natural uncertainty.

1- 2- Contributions

Based on the literature review, the uncertainty of spinning reserves is not considered in the optimal bidding strategy problem. It is expected that considerations for DR and spinning reserve uncertainty would influence bidding parameters, spinning reserve prices, and GENCOs profits. Accordingly, the novelties of this study are

1. Modelling the spinning reserve uncertainty
2. Investigation of the effects of spinning reserve uncertainty on optimal bidding strategy problem
3. Investigation of the effects of EV parking as DR on optimal bidding strategy problem
4. Solving the transmission-constrained optimal bidding strategy problem using a heuristic optimization algorithm

The objection of this study is solving the bidding strategy problem considering transmission constraints, DR, and spinning reserve uncertainty based on a heuristic approach. An actual spinning reserve model using normal distribution is proposed and three case studies are presented.

Next, in section 2, the formulation is presented and the optimization algorithm is discussed in section 3. Section 4 presents the results and finally, in section 5, the conclusion is discussed.

2- Problem formulation

To arrive the objection, three cases are considered:

Case (a): Bidding strategy of one GENCO with and without spinning reserve uncertainty

Case (b): Bidding strategy of three GENCO with considerations for transmission constraints

Case (c): Bidding strategy of one GENCO with considerations for EV parking as DR programs

2- 1- Spinning reserve uncertainty modeling

Normally, the spinning reserve commitment probability is based on a lower probability for higher values of spinning reserve request and a normal distribution function is used [41], as shown in Fig. 1, where the spinning reserve request is changed from zero to 10% of demand at different probabilities. Accordingly, three conditions may occur for the treatment of spinning reserve:

1. Fixed spinning reserve request (10% of demand) and fixed probability (5%) [1-10].
2. Fixed spinning reserve request (10% of demand) and variable probability [41].
3. Variable spinning reserve request (zero to 10% of demand) and variable probability, as proposed in this study.

2- 2- Day-ahead energy market

The case function of a GENCO with thermal units is:

$$f(P(i,t)) = a_i P^2(i,t) + b_i P(i,t) + c_i \quad (1)$$

Then using derivation of Eq (1), MCP is calculated [42, 43]

$$\partial f(P(i,t))/\partial P(i,t)=\rho(i,t)=2a_iP(i,t)+b_i \tag{2}$$

where $\rho(i,t)$ is the initial bidding point of TGU i^{th} owner.

As (α_{jt} , β_{jt}) are bidding parameters of GENCO, the bidding price is [44, 45]

$$\rho_{jt}=\alpha_{jt}+\beta_{jt}TP_{jt} \tag{3}$$

As the profit of TGU i^{th} in energy market is

$$\begin{aligned}PF(i,t)&=\rho_{jt}P(i,t)-f\left(P(i,t)\right)=\\&-a_iP^2(i,t)+\left(\rho_{jt}-b_i\right)P(i,t)-c_i\end{aligned} \tag{4}$$

and to achieve positive profit of TGU i^{th}

$$\rho_{jt}>b_i \tag{5}$$

2- 2- 1- Single-sided auction

Under the single-sided auction, MCP_t and TP_{jt} are [1, 16]

$$MCP_t=\alpha_{jt}+\beta_{jt}TP_{jt}\quad j=1,\dots,N_s \tag{6}$$

$$PD_t=\sum_{j=1}^{N_s}TP_{jt} \tag{7}$$

then,

$$MCP_t=\left(\sum_{j=1}^{N_s}\alpha_{jt}/\beta_{jt}+PD_t\right)/\sum_{j=1}^{N_s}1/\beta_{jt} \tag{8}$$

$$TP_{jt}=\left(MCP_t-\alpha_{jt}\right)/\beta_{jt} \tag{9}$$

$$TP_{j\min}\le TP_{jt}\le TP_{j\max} \tag{10}$$

2- 2- 2- Double-sided auction

Under double-sided auctions, large customers bid a curve ($\phi_{kt}-\varphi_{kt}TL_{kt}$) to the ISO [1] and market parameters are calculated as

$$MCP_t=\frac{\left(\sum_{j=1}^{N_s}\alpha_{jt}/\beta_{jt}+\sum_{k=1}^{N_c}\phi_{kt}/\varphi_{kt}+PD_t\right)}{\left(\sum_{j=1}^{N_s}1/\beta_{jt}+\sum_{k=1}^{N_c}1/\varphi_{kt}\right)} \tag{11}$$

$$TL_{kt}=\left(\phi_{kt}-MCP_t\right)/\varphi_{kt} \tag{12}$$

$$TL_{k\min}\le TL_{kt}\le TL_{k\max} \tag{13}$$

2- 3- Spinning reserve auction

In this section, the spinning reserve bidding strategy is modeled with and without considerations for uncertainty.

Non-negative parameters (γ_{jt} , η_{jt}) are bid for spinning reserve by a GENCO j^{th} at hour t and,

$$\rho^r_{jt}=\gamma_{jt}+re\eta_{jt} \tag{14}$$

If the probability of spinning reserve request is variable throughout the day,

$$\rho^r_{jt}=\gamma_{jt}+re(t)\eta_{jt} \tag{15}$$

where $re(t)$ must be predicated using artificial neural network (ANN) as discussed in [43].

From ISO view, the objective function is:

$$\min\sum_{j=1}^{N_s}RP_tTR_{jt} \tag{16}$$

subject to

$$\sum_{j=1}^{N_s}TR_{jt}\ge R(t) \tag{17}$$

$$TR_{jt} \le TR_{j\max} \tag{18}$$

$$TR_{j\max} = \sum_{i=1}^{N} I(i,t)P_{\max}(i) - TP_{jt} \tag{19}$$

The spinning reserve price is then equal to the highest $(\gamma_j + re(t)\eta_j)$ of the successful bidders.

When both $re(t)$ and spinning reserve requests are variable, RP_t modeling is changed as noted in Ref. [47]. Then, m scenarios are defined for $re(t)$ and $R(i,t)$ and the cost function of spinning reserve is

$$\begin{aligned} C\left(R(i,t)\right) &= \sum_{m=1}^{M}(1-re_m(t))f\left(P(i,t)\right)+ \\ & re_m(t)\left(f\left(P(i,t)+R(m,i,t)\right)\right) \\ & -f\left(P(i,t)\right) \\ &= \sum_{m=1}^{M} re_m(t)\left[f\left(P(i,t)+R(m,i,t)\right)-f\left(P(i,t)\right)\right] \end{aligned} \tag{20}$$

where

$$R(m,i,t) = mR(i,t)/100 \tag{21}$$

The RP_t is determined by the derivative of cost function

$$\begin{aligned} \partial C\left(R(i,t)\right)/\partial R(m,i,t) = \rho_{jt}^{r} = \\ \sum_{m=1}^{M} 2re_m(t)a_i P(i,t) + re_m(t)b_i + \\ 2re_m(t)a_i R(m,i,t) \end{aligned} \tag{22}$$

Then, non-negative parameters (γ_{jt}, η_{jt}) are used by GENCO j[th] at hour t and, the spinning reserve bidding price is

$$\rho_{jt}^{r} = \gamma_{jt} + \eta_{jt} TR_{jt} \tag{23}$$

As the profit of TGU i^{th} in spinning reserve market is

$$\begin{aligned} PF^{r}(i,t) &= \sum_{m=1}^{M} \rho_{jt}^{r} R(m,i,t) - C\left(R(m,i,t)\right) \\ &= \sum_{m=1}^{M} -re_m(t)a_i R^2(m,i,t) + \\ & \left(\rho_{jt}^{r} - re_m(t)\left(2a_i P(i,t)+b_i\right)\right)R(m,i,t) \end{aligned} \tag{24}$$

to achieve positive profit of TGU i^{th}

$$\rho_{jt}^{r} > \left(2a_i P(i,t) + b_i\right)\sum_{m=1}^{M} m re_m(t)/100 \tag{25}$$

Next, RP_t and TR_{jt} are calculated for N_s GENCOs [2]

$$RP_t = \gamma_{jt} + \eta_{jt} TR_{jt} \quad j = 1,\dots,N_s \tag{26}$$

$$R(t) = \sum_{j=1}^{N_s} TR_{jt} \tag{27}$$

then

$$RP_t = \left(\sum_{j=1}^{N_s} \gamma_{jt}/\eta_{jt} + R(t)\right) / \sum_{j=1}^{N_s} 1/\eta_{jt} \tag{28}$$

$$TR_{jt} = \left(RP_t - \gamma_{jt}\right)/\eta_{jt} \tag{29}$$

2- 4- The objective function of GENCO

Obviously, according to forecasted bidding parameters of other opponents, a GENCO tries to maximize its profit when the price-based unit commitment (PBUC) problem is solved along with the determination of $\alpha_{jt}, \beta_{jt}, \gamma_{jt}, \eta_{jt}$. The objective function for PBUC problem is [48]

$$\max\left\{PF = RV - TC\right\} \tag{30}$$

$$RV = \sum_{t=1}^{T} MCP_t TP_{jt} + RP_t TR_{jt} \tag{31}$$

$$\begin{aligned} TC = \sum_{t=1}^{T}\sum_{i=1}^{N} (1-re(t))f\left(P(i,t)\right)+ \\ re(t)\left(f\left(P(i,t)+R(i,t)\right)\right)+ \\ SU(i,t)I(i,t)\left(1-I(i,t-1)\right) \end{aligned} \tag{32}$$

When both $re(t)$ and spinning reserve request are variable, the total cost is changed as

$$TC = \sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{i=1}^{N} re_m \left(f \left(P(i,t) + R(m,i,t) \right) \right) + SU(i,t) I(i,t) \left(1 - I(i,t-1)\right) \quad (33)$$

$$\sum_{i=1}^{N} R(i,t) = TR_{jt} \quad (34)$$

and

$$SU(i,t) = \begin{cases} HSC(i) & T^{off}(i,t) \le CST(i) + MDT(i) \\ CSC(\text{i}) & T^{off}(i,t) > CST(i) + MDT(i) \end{cases} \quad (35)$$

$$I(i,0) = IS(i) \quad (36)$$

The following constraints must be met by GENCO j[th] [49]

$$\sum_{i=1}^{N} P(i,t) = TP_{jt} \quad (37)$$

$$P_{\min}(i) I(i,t) \le P(i,t) \le P_{\max}(i) \quad (38)$$

$$\sum_{i=1}^{N} R(i,t) = TR_{jt} \quad (39)$$

$$T^{on}(i,t) \ge MUT(i) \quad (40)$$

$$T^{off}(i,t) \ge MDT(i) \quad (41)$$

2- 5- Transmission constraint

According to transmission constraint, power flow between buses u and v must be limited

$$-P_{uv-\max} \le P_{uv}(t) \le P_{uv-\max} \quad (42)$$

where

$$P_{uv}(t) = 1 / X_{uv} \left(\delta_u(t) - \delta_v(t) \right) \quad (43)$$

and demand constraint described by Eq. (5) must be satisfied.

In DC load flow equation,

$$\begin{bmatrix} P_{1-inj} \\ . \\ P_{u-inj} \\ . \\ P_{N_b-inj} \end{bmatrix} = [B] \begin{bmatrix} \delta_1 \\ . \\ \delta_u \\ . \\ \delta_{N_b} \end{bmatrix} = \begin{bmatrix} b_{11} & . & b_{1u} & . & b_{1N_b} \\ . & . & . & . & . \\ b_{u1} & . & . & . & b_{uN_b} \\ . & . & . & . & . \\ b_{N_b1} & . & . & . & b_{N_bN_b} \end{bmatrix} \begin{bmatrix} \delta_1 \\ . \\ \delta_u \\ . \\ \delta_{N_b} \end{bmatrix} \quad (44)$$

where b_{uu} is sum of susceptances magnitude connected to bus u and b_{uv} is the negative of susceptance magnitude between buses u and v. Also, P_{u-inj} is injected power of bus u.

It is noted that DC load flow equations are formulated as discussed in the Appendix.

Based on the assumption that $\delta_1 = 0$, then, Eq. (44) is revised as

$$\begin{bmatrix} P_{2-inj} \\ . \\ P_{u-inj} \\ . \\ P_{N_b-inj} \end{bmatrix} = \begin{bmatrix} b_{22} & . & b_{2u} & . & b_{2N_b} \\ . & . & . & . & . \\ b_{u2} & . & . & . & b_{uv} \\ . & . & . & . & . \\ b_{N_b2} & . & . & . & b_{N_bN_b} \end{bmatrix} \begin{bmatrix} \delta_2 \\ . \\ \delta_u \\ . \\ \delta_{N_b} \end{bmatrix} \quad (45)$$

then,

$$\begin{bmatrix} \delta_2 \\ . \\ \delta_u \\ . \\ \delta_{N_b} \end{bmatrix} = [Z] \begin{bmatrix} P_{2-inj} \\ . \\ P_{u-inj} \\ . \\ P_{N_b-inj} \end{bmatrix} \quad (46)$$

$$[Z] = \begin{bmatrix} z_{22} & . & z_{2u} & . & z_{2N_b} \\ . & . & . & . & . \\ z_{u2} & . & . & . & z_{uv} \\ . & . & . & . & . \\ z_{N_b2} & . & . & . & z_{N_bN_b} \end{bmatrix} = \begin{bmatrix} b_{22} & . & b_{2u} & . & b_{2N_b} \\ . & . & . & . & . \\ b_{u2} & . & . & . & b_{uv} \\ . & . & . & . & . \\ b_{N_b2} & . & . & . & b_{N_bN_b} \end{bmatrix}^{-1} \quad (47)$$

2- 6- Demand response modelling

In this study, an EV parking is proposed to investigate the effects of DR programs on bidding strategy problem. As noted earlier, EV parking could affect bidding parameters due to significant demand uncertainty. PEV owners profits are gained from buying energy (charging) at lower energy prices and selling (discharging) at higher energy prices.

After receiving the required parameters from EVs, charging/discharging scheduling is calculated where EVs limitations should be satisfied [50] as listed below:

1. SOC limits:

$$SOC_{\min,q} \le SOC_{qt} \le SOC_{\max,q} \tag{48}$$

2. Charging/discharging rate limits:

$$P_{C,qt} \le P_{C-\max,q} \tag{49}$$

$$P_{D,qt} \le P_{D-\max,q} \tag{50}$$

3. Parking presence:

$$T_{P,q} \le T_{P-\max,q} \tag{51}$$

$$T_{P,q} = t_d - t_a \tag{52}$$

4. Charging/discharging switching number

$$Sw_q \le Sw_{\max,q} \tag{53}$$

3- Optimization algorithm

In this section, the heuristic optimization algorithm is presented. It is noted that for Cases (a) and (c) the heuristic optimization algorithm examined in [11] is modified to solve the bidding strategy problem with considerations for spinning reserve uncertainty. However, a heuristic approach is developed for the transmission-constrained optimal bidding strategy problem (Case(b)).

3- 1- Case (a): Optimal bidding strategy of a GENCO with and without spinning reserve uncertainty.

As the optimization algorithm is applied to GENCO 1, α_{2t}, β_{2t} and α_{3t}, β_{3t} remain constants and a set of 96 parameters must be determined for GENCO 1.

$$S = \begin{bmatrix} \alpha_1 & \beta_1 & \gamma_1 & \eta_1 \\ \alpha_2 & \beta_2 & \gamma_2 & \eta_2 \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_{24} & \beta_{24} & \gamma_{24} & \eta_{24} \end{bmatrix} \tag{54}$$

3- 1- 1- Without spinning reserve uncertainty

In this section, the probability of requesting reserve is assumed fixed. The procedure of optimization is detailed in our previous paper [11] and summarized below:

The output power of EV parking is scheduled by parking owner and therefore, *TP* is changed. It is noted that, parking owners schedule output power of EVs according to forecasted *MCP*.

Maximizing revenue as $Max\left\{MCP_t TP_{1t}\right\}$

To maximize the above equation, GA is used [51-54].

Solving PBUC for GENCO 1 according to determined *MCP* and *TP*. It is noted that the details of PBUC algorithm are discussed in our previous papers [55, 56].

TR is calculated according to output power of units. Then, bidding parameters for the reserve market are submitted by GENCO 1 [11].

The PBUC problem is solved for GENCO j[th]. To do this, the heuristic optimization algorithm discussed in Section 3.1 is used to maximize profit. In this step, GENCO j[th] may change its bidding parameters.

If the bidding parameters of GENCO j[th] are changed, it submits new bidding parameters to ISO, and clearing market is done. Then, go to step 4.

3.1.1.1 Single-sided auction [11]

I. The initial bidding parameters of GENCO 1 must be determined while the revenue is maximized. It means that GENCO j[th] attempts to maximize its *TP* at the maximum possible *MCP*.

$$\max\left\{MCP_t TP_{1t}\right\} \tag{55}$$

$$MCP_t = \left(\sum_{j=1}^{Ns} \alpha_{jt} / \beta_{jt} + PD_t\right) / \sum_{j=1}^{Ns} 1/\beta_{jt} = \left(\alpha_{1t} + A_t \beta_{1t}\right) / \left(1 + B_t \beta_{1t}\right) \tag{56}$$

$$TP_{1t} = \left(MCP_t - \alpha_{1t}\right) / \beta_{1t} = \left(A_t - \alpha_{1t} B_t\right) / \left(1 + B_t \beta_{1t}\right) \tag{57}$$

where

$$A_t = \sum_{j=2}^{Ns} \alpha_{jt} / \beta_{jt} + PD_t \tag{58}$$

$$B_t = \sum_{j=2}^{Ns} 1 / \beta_{jt} \tag{59}$$

To find α_{1t}, β_{1t}, the GA is used [51-54], where initial population=20 and crossover rate is at 80% and, convergence is reached when fitness function (*FF*) tolerance is lower than 10^{-6}.

II. After determining α_{1t}, β_{1t}, other parameters such as $TP_{1t}, TP_{2t}, TP_{3t}$, and MCP_t are calculated.

III. The PBUC problem of GENCO 1 with considerations for calculated MCP_t and TP_{1t} is solved using the heuristic optimization algorithm developed [55, 56]. Note that the spinning reserve constraint is not considered because TR_{1t} is not determined yet.

IV. Due to shutting down some TGUs in step 3, TP_{1t} will reduce to TP_{1t-new}. So, the following optimization problem is solved using GA to find new α_{1t}, β_{1t} [11]

$$\max\left\{MCP_t = \left(\alpha_{1t} + A_t \beta_{1t}\right) / \left(1 + B_t \beta_{1t}\right)\right\} \tag{60}$$

subject to

$$TP_{1t} = \left(A_t - \alpha_{1t} B_t\right) / \left(1 + B_t \beta_{1t}\right) = TP_{1t-new} \tag{61}$$

After determining α_{1t}, β_{1t}, other parameters such as TP_{1t}, TP_{2t}, TP_{3t}, and MCP_t are calculated.

V. Steps 3 and 4 are repeated until the bidding strategy of GENCO 1 is not changed. Then, the profit of GENCO 1 is calculated and other parameters of GENCOs are determined.

3.1.1.2 Double-sided auction

The procedure of optimal bidding strategy for double-sided auction is similar to single-sided auction (Section 3.1.1(I)), but,

$$A_t = \sum_{j=2}^{Ns} \alpha_{jt} / \beta_{jt} + PD_t + \sum_{m=1}^{Nc} \phi_{mt} / \varphi_{mt} \tag{62}$$

$$B_t = \sum_{j=2}^{Ns} 1 / \beta_{jt} + \sum_{m=1}^{Nc} 1 / \varphi_{mt} \tag{63}$$

3- 1- 2- With spinning reserve uncertainty

Similar to Section 3.1.1 (I), TP_{1t} and MCP_t are determined, but RP_t and TR_{1t} must be calculated as discussed next.

I. The initial bidding parameters of GENCO 1 for the spinning reserve market must be determined while the revenue is maximized. It means that GENCO j[th] attempts to maximize its TR at the maximum possible RP.

$$\max\left\{RP_t TR_{1t}\right\} \tag{64}$$

$$RP_t = \left(R(t) + \sum_{j=1}^{N_s} \gamma_{jt} / \eta_{jt}\right) / \sum_{j=1}^{N_s} 1 / \eta_{jt} = \left(\gamma_{1t} + A_t' \eta_{1t}\right) / \left(1 + B_t' \eta_{1t}\right) \tag{65}$$

$$TR_{1t} = \left(RP_t - \gamma_{1t}\right) / \beta_{1t} = \left(A_t' - \gamma_{1t} B_t'\right) / \left(1 + B_t' \eta_{1t}\right) \tag{66}$$

where

$$A_t' = \sum_{j=2}^{Ns} \gamma_{jt} / \eta_{jt} + R(t) \tag{67}$$

$$B_t' = \sum_{j=2}^{Ns} 1 / \eta_{jt} \tag{68}$$

The GA is used to find γ_{1t}, η_{1t} where initial population=20 and crossover rate is at 80% and, convergence is reached when fitness function (FF) tolerance is lower than 10^{-6}.

II. After determining γ_{1t}, η_{1t}, other parameters such as $TR_{1t}, TR_{2t}, TR_{3t}$, and RP_t are calculated.

As spinning reserve uncertainty is considered, the *FF* of $R(i,t)$ is modified as

$$FF_i\left(R(i,t)\right) = PF^r(i,t) = RP(t) R(i,t) - C\left(R(i,t)\right) \tag{69}$$

$$C\left(R(i,t)\right) = \sum_{m=1}^{M} re_m(t)\left[f\left(P(i,t) + R(m,i,t)\right) - f\left(P(i,t)\right)\right] \tag{70}$$

The GA is used to find $R^*(i,t)$ where initial population=20 and crossover rate is at 80% and, convergence is reached when fitness function (*FF*) tolerance is lower than 10^{-6}.

3- 2- Case (b): Optimal bidding strategy of three GENCOs with considerations for transmission constraints

In this case, three GENCOs compete in energy and spinning reserve markets with considerations for transmission constraints and spinning reserve uncertainty. The optimal bidding strategy of three GENCOs is conducted, based on the flowchart shown in Fig. 2,

I. Initial bidding parameters of GENCOs are determined.

II. j=1

III. GENCO j^{th} is chosen and bidding parameters are submitted to ISO. Then, TP, MCP, RP, and TR are calculated.

IV. The PBUC problem is solved for GENCO j^{th}. To do this, the heuristic optimization algorithm discussed in Section 3.1 is used to maximize profit. In this step, GENCO j^{th} may change its bidding parameters.

V. If the bidding parameters of GENCO j^{th} are changed, it submits new bidding parameters to ISO, and the clearing market is done. Then, go to step 4.

If bidding parameters of GENCO j^{th} are not changed, j=j+1 and go to step III.

VI. Steps III to V are continued until all GENCOs are selected.

VII. After the first iteration of the bidding strategy of all GENCOs, ISO checks transmission, demand, and spinning reserve requirement constraints. To satisfy transmission constraints, ISO forces GENCOs to change their output power, but it is better for GENCOs to change their output power as less as possible. Therefore, the objective function for ISO is defined as

$$Min\left\{\sum_{u=1}^{N_b}\left(P_n(u,t)-P(u,t)\right)^2\right\} \tag{71}$$

subject to

$$\left|P_{uv}(t)\right| \le P_{uv-\max} \tag{72}$$

where $\left(P_n(u,t)-P(u,t)\right)$ is the difference between power produced by TGU u^{th} at hour t ($P(u,t)$) and new power produced by TGU u^{th} due to transmission constraints ($P_n(u,t)$).

To solve optimization problem described by Eq. (71), GA is used (Initial population=20, crossover 80%, convergence is reached when *FF* tolerance is lower than 10^{-6}). It means that transmission constraints are satisfied with minimum changes in energy awarded to GENCOs.

The variable of optimization of this step is $P_n(u,t)$ and, therefore using Eqs. (45)-(47), Eq. (72) is rewritten as

$$\left|\delta_u-\delta_v\right| \le P_{uv-\max}X_{uv} \tag{73}$$

or

$$\begin{aligned}&\det\Big(\left[(z_{2u}-z_{2v})\;...\;(z_{N_bu}-z_{N_bv})\right]\\&\left[P_n(2,t)\quad...\quad P_n(N_b,t)\right]^T\\&-\left[(z_{2u}-z_{2v})\;...\;(z_{N_bu}-z_{N_bv})\right]\\&\left[P_D(2,t)\quad...\quad P_D(N_b,t)\right]^T\Big) \le P_{uv-\max}X_{uv}\end{aligned} \tag{74}$$

VIII. According to transmission constraints, GENCOs may change their bidding strategies. If the bidding parameters of any GENCO are changed, go to step 2, otherwise, the optimal bidding strategy of all GENCOs is reached.

3- 3- Case (c): Optimal bidding strategy of one GENCO with DR programs

In this study, an EV parking is considered to model DR program where this variable demand could not be participated in the bidding strategy because of its natural uncertainty. However, according to EVs behaviours, bidding parameters of GENCOs are changed that should be determined by EV owner or forecasted by GENCOs.

The algorithm of forecasting EV parking scheduling is detailed as follows:

I. Initial bidding strategy is solved by GENCO 1 as discussed in section 3.1 and market price and other bidding parameters are determined.

II. According to calculated market price and statistics EVs data, the scheduling of EV parking is done as detailed in [50].

III. After determining the output power of EV parking, the bidding strategy of GENCO 1 is done as discussed in 3.1 and 3.2.

4- Parametric values and data

The following parametric values and input data are used for the simulation of Case (a)-(c) in this study.

4- 1- TGUs

The TGUs characteristics data are based on Ref. [1] for Cases (a) and (c) and Ref. [57] for Case (b) (Table 2).

4- 2- Power system demand

The needed data for power system demand are based on Ref. [1] for Cases (a) and (c) and Ref. [57] for Case (b) (Table 3).

4- 3- Competitors characteristics

Forecasted GENCOs and large consumers' bidding parameters and other needed data are based on Ref. [1].

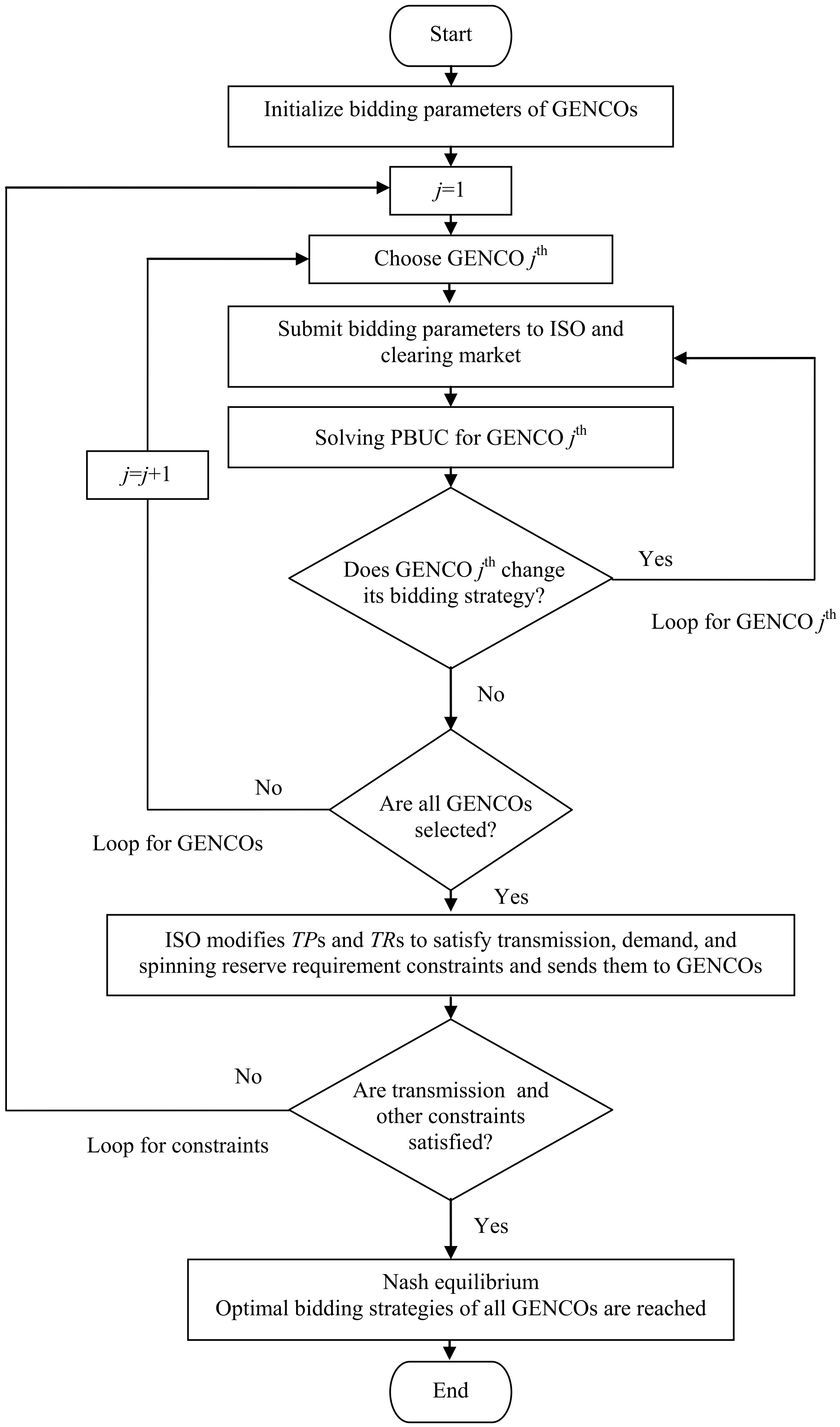


Fig. 2. Flowchart of bidding strategy algorithm of GENCOs in Case (b)

Table 2. Six-TGU power system characteristics [57] for studying Case (b).

GENCO	TGU	Bus	P_{min} (MW)	P_{max} (MW)	a_i ($/(MWh)^2)	b_i ($/MWh)	c_i ($)	MUT (hr)	MDT (hr)	HSC ($)	CSC ($)	IS (hr)
1	G1	1	20	260	0.00463	10.69	142.73	4	3	200	200	4
	G2	3	20	220	0.00612	18.10	218.34	2	2	100	100	2
2	G3	2	20	260	0.00463	10.69	142.73	4	3	200	200	4
	G4	5	5	80	0.01433	37.89	118.82	1	1	70	70	2
3	G5	4	20	220	0.00612	18.10	218.34	2	2	100	100	2
	G6	6	5	80	0.01433	37.89	118.82	1	1	70	70	2

Table 3. Demand characteristics of IEEE six-bus network [57] for studying Case (b).

Hr	PD_t (MW)				hr	PD_t (MW)			
	D_1	D_2	D_3	Total		D_1	D_2	D_3	Total
1	464	155	155	774	13	536	179	179	893
2	428	143	143	714	14	524	175	175	873
3	405	135	135	674	15	518	173	173	863
4	393	131	131	655	16	518	173	173	863
5	381	127	127	635	17	542	181	181	903
6	387	129	129	645	18	488	198	198	885
7	393	131	131	655	19	527	190	190	908
8	417	139	139	694	20	539	188	188	916
9	476	159	159	793	21	550	186	186	923
10	524	175	175	873	22	547	182	182	912
11	536	179	179	893	23	518	173	173	863
12	542	181	181	903	24	482	161	161	804

4- 4- EV parking data

The EV parking data are completely available in [50] for studying Case (c) including the number of EVs, initial charge, arrival and departure times, etc. It is noted that several parameters such as arrival/departure times, age of battery, and initial charge of EVs are random resulting in major demand uncertainty.

5- Simulation results

In this section, simulation results are presented to show the effects of spinning reserve uncertainty and DR programs on bidding strategy. Three cases are studied: (a) the Optimal bidding strategy of one GENCO with and without spinning reserve uncertainty, (b) the optimal bidding strategy of three GENCOs with considerations for transmission constraints and spinning reserve uncertainty, and (c) the optimal bidding strategy of one GENCO with and without DR programs.

5- 1- Case (a): Optimal bidding strategy of a GENCO with and without considerations for spinning reserve uncertainty

5- 1- 1- Without spinning reserve uncertainty

In this case, only GENCOs with the thermal unit are participated in energy and reserve markets. The modified heuristic and deterministic optimization algorithm is applied to the bidding strategy problem and the comparison of profit

Table 4. Case (a) results: Profits comparison for GENCO 1 as compared with other Refs. [1] and [11].

Condition	Profit ($)						
	This study	Heuristic [11]	Improvement (%)	SQP [1]	Improvement (%)	EP [1]	Improvement (%)
Single-sided	226,430	226,330	0.04	217,317	4.20	152,976	48.02
Double-sided	374,210	374,110	0.02	309,597	20.10	284,922	31.30

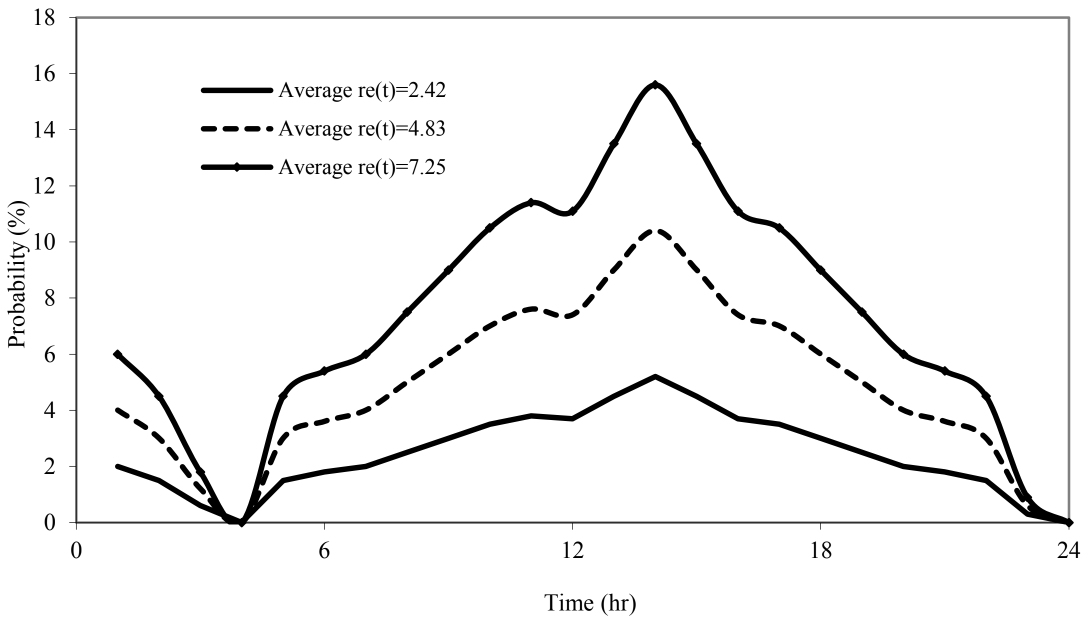


Fig. 3. Predicted spinning reserve request probability curves using ANN [41] for studying Case (a).

in single and double-sided auctions is presented in Table 4.

It shows that GENCO profit is increased by 0.04-48.02 and 0.02-31.30%. For single-sided and double-sided auctions, respectively as compared with Refs. [1] and [11].

To verify the simulation results and for better comparison, output power, MCP , and TP of GENCO under single-sided auction are presented in Tables 5 and 6.

As shown in Table 5, TGU 2 has been ON at hr 24 with 150 MW, whereas it is OFF in Ref. [11]. Also, according to Table 6, MCP and TP are increased as compared with [1] and [11].

5- 1- 2- With spinning reserve uncertainty

In this case, spinning reserve uncertainty is considered and simulation results are presented under two conditions:

I. Fixed spinning reserve request and variable probability

To show the effects of $re(t)$ on bidding strategy of one GENCO, $re(t)$ varies during a 24-hr period when the spinning reserve requirement is fixed at 10% of demand. In this study, the prediction $re(t)$ is utilized using ANN [41] as shown in Fig. 3.

The effects of variables $re(t)$ on profit and spinning reserve prices are presented in Table 7. It is determined that with considerations for variable $re(t)$:

1. $re(t)$ increase results in higher $RP(t)$
2. $re(t)$ increase results in higher $C\left(R(i,t)\right)$
3. In a single-sided auction, when the average of $re(t)$ is 7.25% (more than 5% of the base case), the profit of GENCO 1 is improved by 0.10% and the profit of spinning reserve is increased. In comparison, in the double-sided auction, when the average of $re(t)$ is 7.25%, the profit of GENCO 1 is decreased as compared with the base case, and the profit of the spinning reserve is decreased. This occurrence is due to the fact that $RP(t)$ is zero ($re(t)=0$) at 4 and 24 hr based on Fig. 3 and therefore TR_1 is reduced from 546 to 408 MW.

Table 5. Case (a) results: output powers for 10-thermal units under single-sided auction.

Hour	Output power (MW)										MCP (\$/MWh)	TP_1 (MW)
	1	2	3	4	5	6	7	8	9	10		
1	413	0	0	0	0	0	0	0	0	0	20.13	413
2	431	0	0	0	0	0	0	0	0	0	20.30	430
3	392	0	0	0	0	0	0	0	0	0	19.91	391
4	447	150	0	0	0	0	0	0	0	0	21.97	597
5	455	224	0	0	0	0	0	0	0	0	22.78	678
6	455	221	0	0	0	0	0	0	0	0	22.76	676
7	455	287	0	0	0	0	0	0	0	0	23.41	741
8	455	449	0	0	25	0	0	0	0	0	25.28	928
9	455	455	0	0	48	0	0	0	0	0	25.57	957
10	455	455	0	130	146	0	0	0	0	0	27.86	1186
11	455	455	130	130	155	20	0	0	0	0	29.45	1345
12	455	455	130	130	156	20	0	0	0	0	29.46	1346
13	455	455	130	130	162	0	25	0	0	0	30.12	1412
14	455	455	130	130	116	0	0	0	0	0	28.85	1285
15	455	455	130	105	25	0	0	0	0	0	28.24	1224
16	455	455	130	130	162	58	25	0	0	0	30.14	1414
17	455	455	130	130	162	80	85	55	55	49	32.56	1656
18	455	455	130	130	162	80	0	55	55	55	33.60	1662
19	455	455	130	130	162	80	0	55	55	55	35.07	1662
20	455	455	130	130	162	80	85	55	55	55	33.17	1662
21	455	455	130	130	162	80	36	55	0	0	31.02	1502
22	455	455	130	130	87	0	0	0	0	0	28.57	1257
23	455	321	0	0	0	0	0	0	0	0	23.75	775
24	446	150	0	0	0	0	0	0	0	0	22.85	595

II. Variable spinning reserve request and variable probability

When the spinning reserve request is changed from zero to 10% of demand at different probabilities, the effects of spinning reserve uncertainty on profit and spinning reserve bidding parameters are presented in Table 8. It is determined that with considerations for spinning reserve uncertainty:

1. The costs of the spinning reserve are increased because the spinning reserve is changed from zero to 10% of demand at different probabilities. It is noted that in other studies, the spinning reserve request is fixed at 10% of demand and fixed probability at 5% [1, 2] which leads to lower spinning reserve costs, but in actual electricity markets, the probability associated with spinning reserves is variable, as considered in this study.

2. The average of *RP* is increased. This occurrence is due to the fact that spinning reserve market bidding parameters are determined based on Eq. (28) instead of Eq. (15).

3. Although, the average of RP is increased, but due to increasing the costs of spinning reserve, the profit of GENCO is decreased, as compared with the case with fixed spinning reserve probability.

5- 2- Case (b): Optimal bidding strategy of three GENCOs with considerations for transmission constraints and spinning reserve uncertainty

Three GENCOs with 6 TGUs (Table 2) are considered in Case (b). It is noted that every GENCO has two TGUs (G1 and G2 for GENCO 1, G3 and G4 for GENCO 2, and G5 and G6 for GENCO 3) in an IEEE six-bus network with $P_{base} = 100$ MW and flow limit of 1800 MW (Table 3 and Fig. 4) [57] that is not used in the literature.

The probable spinning reserve is up to 10% of the power system demands under normal distribution. In this study, it is assumed that D_1, D_2, and D_3 may increase by 10% uniformly, as the spinning reserve requirement to be met by GENCOs.

After 10 iterations, maximum possible profits for GENCO 1 (*PF*=\$112,298), GENCO 2 (*PF*=\$89,627), and GENCO 3 (*PF*=\$34,927) with considerations for transmission constraints are reached, as shown in Fig. 5-a. To verify the simulation results, the optimal bidding parameters of GENCOs and other related parameters of energy and spinning reserve markets are shown in Table 9. In Fig. 5-b, the power flow of lines in 24 hours is shown when it is observed that line capacities are not violated and transmission constraints are met.

Table 6. Case (a) results: Bidding parameters of GENCO 1, energy and spinning reserve market prices, and power awarded to GENCO 1 in single-sided auction without spinning reserve uncertainty.

hr	α (\$/MWh)	β (\$/(MWh)^2)	γ (\$/MWh)	η (\$/MWh)	MCP (\$/MWh)	RP (\$/MWh)	TP_1 (MW)	TR_1 (MW)
1	16.00	0.0100	1.31	89	20.13	5.76	413	81
2	16.00	0.0100	1.89	93	20.30	6.54	430	79
3	16.00	0.0100	2.87	93	19.91	7.52	391	71
4	16.00	0.0170	2.87	81	23.62	6.92	448	100
5	16.00	0.0100	2.78	93	22.78	7.43	678	112
6	16.00	0.0100	1.99	87	22.76	6.34	676	114
7	16.00	0.0100	3.65	87	23.41	8.00	741	128
8	16.00	0.0105	4.78	79	25.50	10.00	905	6
9	16.00	0.0110	5.65	79	26.00	10.00	909	0
10	16.00	0.0100	5.89	73	27.86	9.70	1186	16
11	16.00	0.0103	6.53	69	29.64	10.29	1324	7
12	16.00	0.0103	7.29	83	29.65	11.70	1325	6
13	16.00	0.0111	7.29	79	30.81	11.70	1334	0
14	16.00	0.0100	7.99	65	28.85	11.60	1285	46
15	16.00	0.0108	7.19	65	28.65	10.70	1172	152
16	16.00	0.0103	8.39	59	30.33	11.94	1391	22
17	16.00	0.0130	8.99	65	34.39	12.40	1415	0
18	16.00	0.0141	8.99	65	35.94	12.70	1414	0
19	16.00	0.0160	8.99	65	38.57	13.60	1411	0
20	16.00	0.0137	9.67	67	35.33	14.03	1411	0
21	16.00	0.0110	7.89	69	31.58	11.65	1416	0
22	16.00	0.0100	6.63	73	28.57	10.70	1257	75
23	16.00	0.0100	5.09	79	23.75	9.04	775	132
24	16.00	0.0188	4.44	79	24.57	9.10	456	0

Table 7. Case (a) results: The effects of variable on profit and spinning reserve prices.

Auction	Variable $re(t)$	Average $re(t)$ (%)	TR_1 (MW)	TR_1 cost (\$)	Average RP (\$/MWh)	Profit (\$)	Profit improvement (%)
Single-sided	No	5.00	1,147	1,045	9.97	226,330	-
	Yes	2.42	915	428	7.79	223,920	-
	Yes	4.83	915	856	9.69	225,250	-
	Yes	7.25	915	1,285	11.57	226,560	0.10
Double - sided	No	5.00	546	518	10.15	374,110	-
	Yes	2.42	408	130	7.85	372,570	-
	Yes	4.83	408	259	9.80	373,080	-
	Yes	7.25	408	388	11.71	373,580	-

Table 8. Case (a) results: The effects of variable and variable spinning reserve requests on profit and spinning reserve bidding parameters.

Auction	Spinning reserve uncertainty	TR_1 cost ($)	Average RP ($/MWh)	Profit ($)
Single-sided	No	1,045	9.973	226,330
	Yes	3,176	10.661	225,290
Double -sided	No	684	10.335	374,110
	Yes	2,013	11.051	373,880

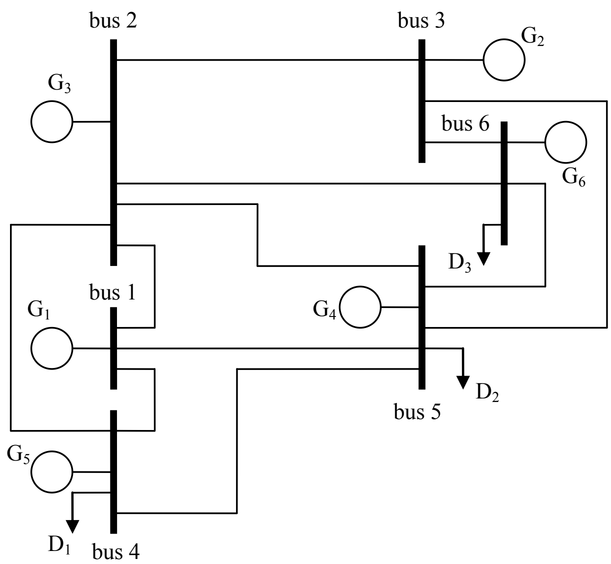


Fig. 4. Schematic of IEEE six-bus network [57] for studying Case (b). GENCO 1: G1 and G2, GENCO 2: G3 and G4, GENCO 3: G5 and G6

Table 9. Case (b) results: Final optimal bidding parameters of GENCOs in energy and spinning reserve markets.

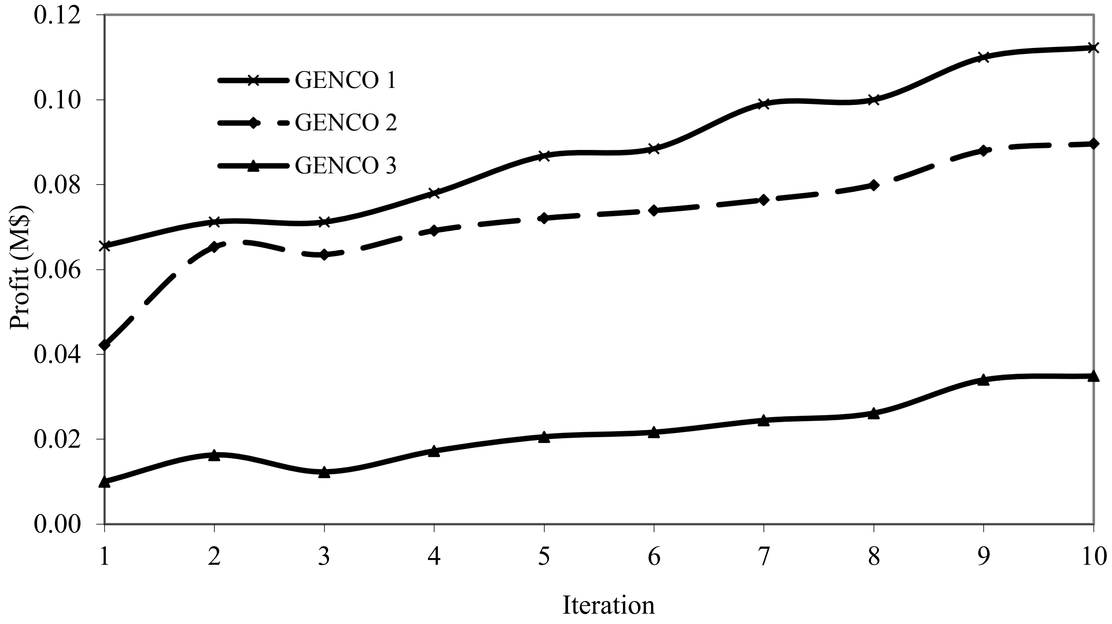
hr	GENCO 1		GENCO 2		GENCO 3		*MCP* ($/kWh)	*RP* ($/kWh)
	TP (MW)	*TR* (MW)	*TP* (MW)	*TR* (MW)	*TP* (MW)	*TR* (MW)		
1	294	77	294	0	294	0	24.99	8.38
2	247	13	247	13	247	0	22.47	8.10
3	227	33	227	33	227	0	22.27	8.21
4	218	42	218	42	218	0	22.18	8.25
5	211	49	211	49	211	7	22.12	8.27
6	215	45	215	45	215	5	22.15	8.24
7	218	42	218	42	218	0	22.18	8.25
8	237	23	237	23	237	0	22.37	8.15
9	313	79	313	0	313	0	25.09	8.38
10	393	87	393	0	393	0	24.62	8.43
11	413	67	413	0	413	0	24.98	8.33
12	423	57	423	0	423	0	25.23	8.28
13	413	67	413	0	413	0	24.98	8.33
14	393	87	393	0	393	0	24.62	8.43
15	383	86	383	0	383	0	24.44	8.43
16	383	86	383	0	383	0	24.44	8.43
17	423	57	423	0	423	0	25.18	8.28
18	340	89	340	68	340	28	39.68	8.48
19	349	91	349	0	349	0	42.95	8.47
20	356	92	356	0	356	0	43.15	8.47
21	363	92	363	0	363	0	43.33	8.47
22	402	78	402	50	402	0	26.22	8.41
23	383	86	383	0	383	0	24.44	8.43
24	383	80	383	0	383	0	24.11	8.42

5- 3- Case (c): Optimal bidding strategy of one GENCO with considerations for EV parking as DR programs

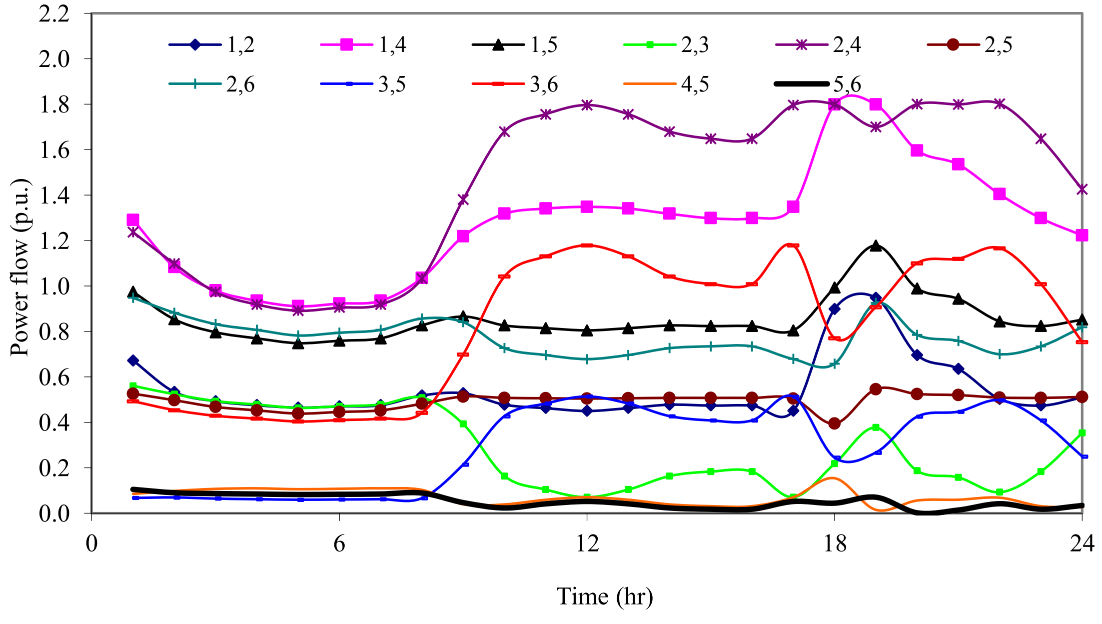
In this case, it is assumed that an EV parking is considered as variable load and, the effects of DR programs on the bidding strategy problem are investigated. The number of EVs is 20,000 and the capacity of each battery and rated charging/discharging power are 16 kWh and 2 kW, respectively [50].

EV parking is a generator/consumer that affect directly GENCOs decisions. It is because the generator/consumer hours are stochastic. For simulation, the MATLAB code run is occurred and the average charging/discharging scheduling of EV parking is presented in Table 10. It is noted that GENCOs should forecast EVs behaviors and parking owner decisions.

In Table 10, a forecasted output power of EV parking is shown. The output power of EV parking is forecasted according to several factors such as market price, arrival/



(a)



(b)

Fig. 5. Case (b) results: a) Convergence of profits for GENCO 1, GENCO 2, and GENCO 3 . b) Power flow of lines of IEEE six-bus network in a 24-hr period, when transmission constraints and spinning reserve uncertainty are considered

Table 6. Case (a) results: Bidding parameters of GENCO 1, energy and spinning reserve market prices, and power awarded to GENCO 1 in single-sided auction without spinning reserve uncertainty.

hr	Price (single-sided auction) ($/MWh)			SOC of a sample EV (%)	Output power (MW)			
					Sample EV (No. 22)		Total EVs	
	MCP	Charging	Discharging		Charge	Discharge	Charge	Discharge
1	20.13	18.12	19.35	60	-	-	-	-
2	20.30	18.27	18.85	60	-	-	-	-
3	19.91	17.92	37.00	60	-	-	-	-
4	23.62	21.26	37.12	60	-	-	-	-
5	22.78	20.50	26.37	60	-	-	-	-
6	22.76	20.48	22.38	60	-	-	-	-
7	23.41	21.07	32.03	40	-	0.40	-	6.60
8	25.50	22.95	21.55	40	-	-	-	6.10
9	26.00	23.40	34.86	60	0.40	-	24.68	-
10	27.86	25.07	33.70	60	-	-	14.43	-
11	29.64	26.68	30.33	60	-	-	6.60	-
12	29.65	26.69	38.79	80	0.40	-	-	2.00
13	30.81	27.73	29.30	80	-	-	31.19	-
14	28.85	25.97	41.49	90	0.40	-	12.67	-
15	28.65	25.79	48.44	90	-	-	17.07	-
16	30.33	27.30	33.44	90	-	-	4.00	-
17	34.39	30.95	30.70	90	-	-	5.00	-
18	35.94	32.35	47.59	90	-	-	36.26	-
19	38.57	34.71	39.87	90	-	-	39.60	-
20	35.33	31.80	40.08	90	-	-	1.99	-
21	31.58	28.42	62.63	90	-	-	-	-
22	28.57	25.71	45.20	90	-	-	-	-
23	23.75	21.38	22.84	90	-	-	-	1.56
24	24.57	22.11	31.64	90	-	-	-	-

departure times of EVs, initial *SOC* of EV batteries, and so on. It is shown from Table 10 that,

1. The final SOC of each EV should be 90%. The SOC of a sample EV is shown and the SOC limits are satisfied. It is noted that the initial SOC of EVs is random [50].

2. According to forecasted *MCP*, charging/discharging prices determined by EV parking owner [50], initial SOC of EVs, and arrival/departure hours of EVs, the output powers of a sample EV and all EVs are shown. Naturally, the charging hours are more than the discharging hours. However, EV parking owner benefits from its charging/discharging pattern that is based on EVs parameters and selling power to EVs and forecasted *MCP*.

3. The EV parking not only affects the demand curve but also the bidding parameters of GENCOs. It should be noted that some EV parameters are random and therefore, the bidding strategy problem should be solved by GENCOs accordingly.

A comparison of bidding strategy results with and without EV parking is presented in Table 11 where it is concluded that:

1. Obviously, EV parking owners benefit from selling

Table 11. Case (c) results: Bidding strategy results comparison with and without DR under single and double-sided auctions.

Conditions		Total TP_1 (MW)	Average MCP ($/MWh)	GENCO 1 profit ($)	Total TR_1 (MW)	Average RP ($/MWh)	Parking owner revenue ($)
Auction	DR						
Single-sided	No	24,163	27.62	226,430	1147	9.97	0
	Yes	24,205	27.63	227,881	1085	9.96	2,804
Double-sided	No	29,901	31.83	374,210	546	10.34	0
	Yes	30,002	31.84	376,012	521	10.32	3,385

power to EVs, and profits of $2,804 and $3,385 are reached.

2. As total demand is increased, TP_1 and MCP are increased due to changing bidding parameters of GENCO 1.

3. Considering DR programs, the output powers of TGUs are increased, and therefore, their spinning reserve capacities are decreased and then, TR_1 and RP are decreased.

6- Conclusion

In this study, the optimal bidding strategy problem for GENCOs in energy and spinning reserve markets with considerations for transmission constraints, DR programs, and spinning reserve uncertainty is solved when a heuristic optimization algorithm is developed.

In this study, two demand uncertainties are modeled and simulated: (1) Spinning reserve uncertainty in request probability and quantity. (2) EV parking as a DR program with stochastic output power. From the results, it is concluded that:

Due to variable probability associated with spinning reserve and variable spinning reserve request, the spinning reserve uncertainty is considered is this study and, it is concluded that three types of spinning reserve uncertainty result in different results (bidding power, market price, and GENCO profit) that could not be reached in other studies.

It is proposed that to solve the bidding strategy problem in a particular network, providing the required spinning reserve is necessary and, the heuristic optimization algorithm is successfully examined for optimal bidding strategy problem in energy and spinning reserve markets for three GENCOs with considerations for transmission constraints.

When EV parking is added to the bidding strategy problem, it is concluded that DR program forecasting is very important for GENCOs. Specially, in the case of EV parking, both demand quantity and hours are stochastic and also generation/consumption hours. Unappropriated forecasting and decisions result in decreasing GENCOs profits.

For future works, renewable energy resources and combined heat and power units could be added to the optimal bidding strategy problem. Also, the local heat market could be added to the bidding strategy problem when the heat network may be considered.

Nomenclature

a, b, c	Cost function coefficients
B	Susceptance
b	Susceptance between buses
C	Cost
CSC	Cold start cost
CST	Cold start time
Det	Determinant
FF	Fitness function
f	Fuel cost
G	Conductance
HSC	Hot start cost
i	TGU index
I	Initial Index
j	GENCO Index
k	Consumer index
m	Scenario index
M	Total number of scenarios
MCP	Margined cost price
MDT	Minimum down time
MUT	Minimum up time

N	TGUs number
N_b	Buses number
N_c	Consumers number
N_s	GENCOs number
PD	Power demand
PF	Profit
P_C	Charge power
P_D	Discharge power
q	EV index
R	Reserve
RV	Revenue
re	Reserve probability
RP	Reserve price
SOC	State of charge
SU	Start-up cost
Sw	Switching number of EV battery
t	Time index
T	Total time
TC	Total cost
TP	Power awarded to GENCO
TL	Power awarded to consumer
TR	Reserve awarded to GENCO
t_a	Arrival time
t_d	Departure time
T_P	Time in parking
u, v	Bus index
X	Reactance
Z	Inverse of B matrix
$\alpha,\beta,\gamma,\eta,\phi,\varphi$	Bidding parameters
δ	Angle of voltage
ρ	Marginal price

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