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Reserve market scheduling considering both capacity and energy bids of reserve

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ABSTRACT

In conventional Ancillary Service Markets (ASM), where Independent System Operator (ISO) purchases requirements for system safe and reliable operation, capacity and energy of reserves have always been considered as individual commodities. Market participants offer their capacity bids and energy bids to the ASM, then the ISO decides on purchasing the required capacity using an optimization model based on capacity bids while energy bids are neglected. During the operation time, the ISO has to call some of the purchased capacity to provide required energy for frequency response, and pay them accordingly at their reserve bids. Therefore, the ISO has to pay for both capacity and applied energy while ISO's model considers capacity costs alone, thus it cannot reach the overall optimum point. To develop ISO's model for considering energy bids, an Artificial Neural Network (ANN) based method is proposed in this paper to define a combination of energy and capacity bids to be substituted for solo capacity bids in ISO's model of market. A modified 24-bus IEEE test system is employed to illustrate the proposed methodology.

Introduction

By the restructuring procedure in electrical power markets and decomposing the vertically integrated utilities, system operation and stability were assigned to the ISO meanwhile the ISO does not have the authorization for free access to the system components. So the ASMs were formed to be a place for ISO to purchase the system operation requirements. Market participants bid to the ASM for providing the capacity and energy, and then the ISO runs the market model to minimize the total operation cost subject to technical constraints [1–4]. The ISO sets the market model limitations regarding to the system reliability criteria and standards; Adequacy of these constrains should be verified by the dynamic and static simulations of the system [5,6].

In conventional ancillary service markets, the ISO declares the amount of required capacity by stability and reliability studies but the amount of this capacity which is going to be called to produce energy at the operation time is not known before the end of operation time. Because of this lack of information, at the closing time of market, the ISO purchases the required capacity by minimizing the total capacity cost based on the capacity bids alone, and pays the capacity providers at the market clearing price, while energy bids are neglected. Later, during the operation time, ISO has to apply some of this purchased capacity to maintain the system frequency and pay for their applied energy at the proposed energy bids whereas these bids has previously been ignored at the ISO's decision making model. So the ISO's total payment is different from what is optimized in ISO's model of market. So far, a significant amount of work has been done that developed the ASM model, most of them did not take the energy bids into account, some of them tried to consider the reserve energy costs supposing that the reserve will be fully used during the operation time, and some others tried to evaluate the total cost in different scenarios. Nevertheless, determining a mechanism for forecasting and modeling the effects of energy bids on the total operation cost has not been considered.

In conventional ASM models, the ISO ignores the energy bids while models the reserve market for purchasing the reserve capacity. During the operation, ISO has to use some amount of energy of the purchased capacity. Consequently, the reserve providers have to be paid for their used energy; the rate of these payments is their proposed reserve energy bids [1]. This procurement procedure motivates the market participants to propose competitive bids for their capacity to win in the market, and increase their energy price to the highest level to obtain maximum profit. Final result will be a higher total operation cost for ISO. This mechanism is now being used in the deregulated power markets around the world, although there might be some differences which are

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Nomenclature

$CB_{R,g}(R_g)$	bid offers for capacity of reserve
$EB_{R,g}(R_g)$	bid offers for energy of reserve
N_{RP}	number of reserve providers
N_z	number of zones
$N_{line,z}$	number of tie lines between zone z and other zones
N_{hdA}	number of implemented historical data for sensitivity analysis
N_j	number of probable features
R_g	provide reserve by unit g
RE_g	applied energy of unit g
F_i	power flow of line i
R_z^{req}	required reserve at zone Z
I_g	inertia of unit g
I^{Req}	required inertia
APE	absolute percentage error of ANN output
APED	difference between APEs with and without a probable feature
MAPED	mean APED
α_g	frequency drop of unit g
SF	selected features
α^{Nadir}	drop acceleration
GRL_g	ramp limit of unit g
R_g^{max}	maximum proposed reserve by generator g for increasing in its output power
R_g^{min}	maximum proposed reserve by generator g for decreasing in its output power
$\rho_R^{Cap.}$	clearing price for capacity of reserve
$\rho_{R,g}^{Energy}$	clearing price for capacity of reserve
z	zone index
g	generator index
real	index for deterministic parameters
for	index for forecasted parameters

inconsiderable from this standpoint. For instance, in the United States, PJM ISO and Midwest ISO has defined some ceiling for capacity offers of the reserve providers [3,4].

Ref. [1], studied an ASM market for different amounts of reserves' energy which might be applied, and effectively represented the gap between total system operation costs in two cases, first if energy bids were considered in the market model and in second case, if energy bids were neglected. The energy costs over the total costs versus the amounts of applied energy were tabulated. Then, this table was applied for obtaining the total minimum costs. Since that model required the operation data and the amount of called capacity to generate energy, it can only be used for past hours, but does not present a solution for considering the participants' energy bids in upcoming hours. The developed Unit Commitment (UC) in [7], defines the amount of required reserve capacity as a decision variable that controls the robustness of UC; but costs of reserves' applied energy are ignored so the market clearing solution would not reach to the overall optimum. ISO's objective of the proposed model in Refs. [8,9] is minimizing the system operation cost considering AS capacity price, such that participants bid for their capacity as the lost opportunity cost to ASM, that model had ignored the reserve energy bids. Suggested model in [10] presents an ANN based algorithm to forecast required amounts of different types of reserves. Then, it defined the minimization of total market players' bids for energy and capacity as the ISO's objective, assuming that the whole purchased capacity will be implemented. Generally, there are two viewpoints on energy of reserve in current reserve market models. First one ignores the cost of reserves' energy while models the market. The second one assumes that the purchased reserves' capacities will be called to generate energy with their full capacities. Obtained results of the proposed model in this paper represents that none of this assumptions will lead to the optimal equilibrium point. In [11] a traditional model is proposed which simultaneously considers the total cost of energy of power market and reserve capacity price, AS energy costs are remained disregarded. Ref. [12] points to necessitation of considering generation conditions for pre and post contingency, and illustrated the interconnection of economic parameter and frequency control loop performance; for reserve costs, capacity bids alone were taken into account. Ref. [13] considers standpoint of a generation company which models the market to find its optimal strategy. First different scenarios are made; then, the expected profit of the generation company is optimized for each scenario. In that model implemented energy of reserves is neglected. Refs. [14,16] ignore reserves' energy bids while they study the bidding strategies of generation companies in a joint energy and reserve market. Ref. [18] also disregards reserve energy bids while discusses from ISO standpoint.

Lack of a model for considering energy bids in ISO's model of reserve market leaded to a gap between the final settlements and the ISO's objective function for deciding on purchasing reserve at the closing time of market; the final result is deviation from overall optimum point of the market, which is investigated in Ref. [1]. Providing a practicable method for considering the reserve energy costs in ASMs is the target point of this study. Since the amount of applied energy and its effects on market problem is not determined before the operation time a forecasting progress is needed. In this paper a forecasting algorithm based on artificial neural network is employed to estimate the impact of reserve energy payments on total operation costs.

The rest of the paper is organized as follows. Implemented ISO's model in a conventional ASM and its modifications for entrance of the energy bids are introduced in next section. The proposed forecasting algorithm is presented in Section 'Proposed algorithm for determining the combination of energy bids and capacity bids for optimal market operation'. Section 'Numerical results' presents an example and numerical analyses to illustrate the proposed model, and Section 'Conclusion' concludes this paper.

Problem description

Implemented reserve market model in the conventional ASMs

In a power market, it is ISO's responsibility to ensure optimal usage of the system in terms of technical requirements. Welfare maximizing or minimizing the total cost can be considered as the system economic objective function; this optimization is restricted by technical constraints, including the limitations of generation units, power system restrictions and criteria of the system stability [15].

In a general classification, frequency control services are divided into three groups based on performance and response time: 1 – Regulation and frequency response service, with the response time of less than a minute, 2 – Spinning reserve,

Table 1
Frequency control services categories based on response time.

Row	Type of services	Response time
1	Regulation and frequency response	Less than a minute (moment to moment)
2	Spinning reserve	Less than 10 min
3	Non-spinning reserve	Less than 30 min

3 – Non-spinning reserve [10]. This classification may vary in different ASMs around the world; however, it is generally as Table 1.

In order to purchase any of these services, the ASM model can be simultaneously implemented with the markets of other ones and in a more general approach, integrated with power market. For more evaluation accuracy of the proposed method, regulation and frequency response market is alone studied in this paper, although this model is applicable for other mentioned ancillary services; it is also expandable for a simultaneous reserves market. In addition, power market can simply be synchronized needless of any major modification.

For reserve procurement, first ISO studies the dynamic and reliability of the system to determine the requirements which ensure maintaining the system reliable operation. Then, the ISO runs the market and purchases the required capacity from reserve providers. These requirements including required reserve capacity, required inertia, response time, etc. will be applied in reserve market model as constraints. And then, the obtained results will be evaluated by dynamic modeling to confirm its sufficiency or determine the required adjustments, if any [1–3,8,9]. The proposed model in this paper applies an ANN based method to develop the reserve market model, shown in Fig. 1.

ISO's objective function

In the conventional reserve markets, the objective of the ISO is minimizing the total cost of required reserve capacity.

$$\text{ISO's Objective Function}: \quad \text{Min}\sum_{g=1}^{N_{\text{RP}}} \text{CB}_{R,g}(R_g) \tag{1}$$

Market players in a reserve market offer two separate bids, one for capacity and the other for energy [3]. The capacity bids are related to lost opportunity cost of the power producers for not attending to the power market [8], and will be applied at ISO's objective mentioned in (1), while energy bids are related to the condition in which the purchased capacity is asked to generate by the ISO. Reserve providers will be paid at market clearing price for provided capacity while energy payments are pay as bid.

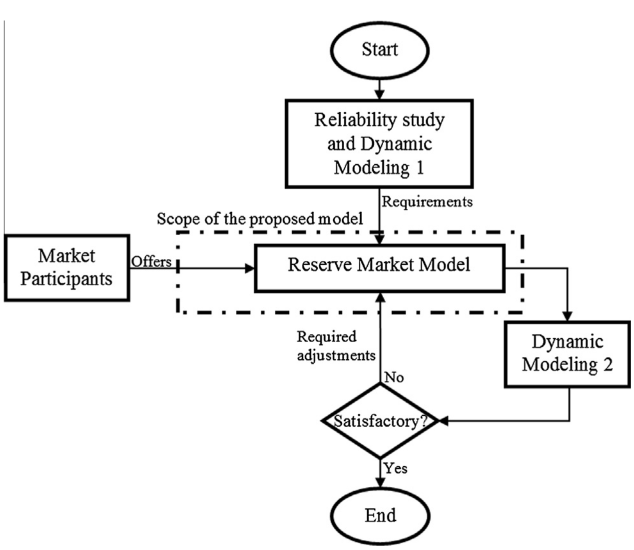

Fig. 1. Reserve procurement procedure and scope of proposed model.

Constraints

There are three general types of constraints that the main problem is restricted by them.

1. Constraints related to generation units

$$\text{Unit constraints}: \begin{cases} R_g^{\min} \leqslant R_g \leqslant R_g^{\max} \\ -\text{GRL}_g \leqslant R_g \leqslant \text{GRL}_g \end{cases} \tag{2}$$

where $R_g^{\max}$ and $R_{g,i}^{\min}$ denote the maximum acceptable increase or decrease in generation by the reserve provider. Generation Ramp Limit (GRL) defines the permitted loading slope of generation unit; and it declares the response time.

2. Power system restrictions

DC Load flow is considered as a determiner of the system requirements and constraints, including lines capacity, transformers capacity, etc.

3. Restrictions related to the system security

These restrictions depend on the characteristic of the system and also market rules and criteria which might vary from market to market [3,4]; i.e. some markets consider enough preparation to ensure system's safe operation in case of one contingency while some other for two. However, reliability studies and dynamic simulation determine the worst contingency condition and enough preparations which should be performed to avoid entering into the operation range of protective relays accordingly. Outage probability of the transmission lines and generation units, and their capacity are the main measures for determining the worst contingency condition. System's security requirements consist of total required reserves (R^{req}), zonal required reserve (R_z^{req}), required inertia (I^{Req}), and the required acceleration ($-\alpha^{\text{Nadir}}$) for compensating the frequency droop [5,8–10]. α is the ratio of power variations to the frequency deviations. To obtain these parameters, at first, dynamic modeling calculates the rate of frequency droop in case of worst contingency condition without implementation of reserves. Then its deviation from the maximum permitted margins by protection system is obtained. Then, the required reserve capacity, inertia and acceleration are determined to maintain this deviation [5]. These required preparations are entered to the model as the security constraints (3).

Security constraints:

$$\begin{cases} F_i^{\min} \leqslant F_i \leqslant F_i^{\max} \\ \sum_{g=1}^{N_{\text{RP},z}} R_g + \sum_{i=1}^{N_{\text{line},z}} (F_i^{\max} - F_i) \geqslant R_z^{\text{req}} \\ \text{Total Required Reserve}: \sum_{g=1}^{N_{\text{RP}}} R_g \geqslant R^{\text{req}} \\ \text{Required Inertia}: \sum_{g=1}^{N_{\text{RP}}} I_g \geqslant I^{\text{Req}} \\ \text{Required response time}: \sum_{g=1}^{N_{\text{RP}}} \alpha_g \geqslant -\alpha^{\text{Nadir}} \end{cases} \tag{3}$$

F_i represents the power flow of transmission lines that must remain in the range of the lines capacity, $F_i^{\max}$ is the maximum available lines capacity. For each line, $F_i^{\max}$ is equal to maximum permitted flow of the line minus its transmission flow from power market.

Maximum permitted line flow is the nominal capacity of the transmission line restricted by the stability criteria. $F_i^{\min}$ is same as $F_i^{\max}$ for the reverse flow direction. Congestion on transmission lines limits the accessibility of reserves and divides system to several zones; second constraint ensures of enough reserve supply for each zone, so that the total internal reserve plus the lines available capacity in order to access to reserve from other zones must be over than the required reserve in that zone. Third limit considers the total required reserve of the system.

In case of worst contingency, system needs to enough Inertia (I^{Req}) and acceleration in the total power generation ($-\alpha^{\mathrm{Nadir}}$). Fourth constraint refers to providing the required inertia for the assurance of the system stability maintenance. For each unit, α_g is the percentage of sensitivity of its output power to the frequency deviations, where the base is system's required acceleration ($-\alpha^{\mathrm{Nadir}}$) for compensation of worst contingency. In other words, α_g is the percentage of inverted droop characteristic [20]. The last constraint refers to the droop characteristic of reserves, which is in form of $\sum_{g=1}^{N_{\mathrm{RP}}^{\mathrm{PFR}}} \alpha_g \geqslant -\alpha^{\mathrm{Nadir}}$ for frequency response service, where α^{Nadir} is taken 100%. For next reserves which will enter to the system in the next steps, this constraint will be in form of $\sum_{g=1}^{N_{\mathrm{RP}}^{\mathrm{SFR}}} \alpha_g \geqslant \alpha^{\mathrm{Recovery}}$. The regulation and frequency response providers must be able to maintain the system frequency during the worst contingency and prevents frequency falls down below the permitted margins then begin to restore the system frequency to its nominal value, afterward, the next reserves in terms of their performance rate will enter to the system respectively, and the faster reserves capacity will be released in order to get ready to confront with the next probable events. Thus rate of frequency recovery must be more than the rate of frequency droop α^{Nadir} [5,20]. Droop and recovery times of the system are specified in Fig. 2, which refers to an incident occurred in England's power system resulting in outage of 1220 MW of the generation capacity on 15th August 1995 at 12:25:30 am [2].

Payments

ISO declares market price and capacity payments by solving the problem and finding the minimum system cost based on the listed constraints (usually through Lagrange relaxation method). Then, after operating the system, payments related to energy will be determined according to the amount of utilized energy of each unit based on the pay as bid. The relation set (4) defines the amount of payment for each part of the reserve:

$$\text{Reserve capacity payment}: \ \rho_R^{\mathrm{Cap.}} * R_g \tag{4.1}$$

$$\text{Reserve energy payment}: \ \rho_R^{\mathrm{Energy}} * \mathrm{RE}_g \tag{4.2}$$

where:

$\rho_R^{\mathrm{Cap.}} =$ (lagrangian coefficient of the related constraint)
$\rho_R^{\mathrm{Energy}} =$ Reserve's energy bid offer of the winner generation unit g

Entrance of the energy bids into the market model

The weakness of mentioned structure in Section 'Implemented Reserve Market Model in the Conventional ASMs' is that the energy bids have no effect on ISO's decision making model for selecting reserve providers, according to (1), while ISO also has to pay them for their applied energy, (4.1) and (4.2). This encourages market players to offer competitive capacity bids to win in the ASM, but to increase their energy bids to make more income. In other words, in conventional ASM, ISO's market model does not fit to its final total payment.

In the following method, instead of solo capacity bids, a combination of capacity bids and energy bids are taken into account in ISO's objective, in order to consider influences of energy costs, relation (5); so the objective of the model becomes more appropriate to the total payments [1].

$$\text{ISO's Objective Function}: \ \mathrm{Min} \sum_{g=1}^{N_{\mathrm{RP}}} \mathrm{CB}_{R,g}(R_g) + X * \mathrm{EB}_{R,g}(R_g) \quad 0 \leqslant X \leqslant 1 \tag{5}$$

If X is taken zero, the problem will be obtained as the conventional methods. In this model, determining the X is major step to make the objective (5). The price of capacity is achieved from resolving the ISO's problem and payments will be as follows:

$$\text{Reserve capacity payment}: \ \left(\rho_R^{\mathrm{Cap.}} - X * \mathrm{EB}_{R,g}\right) * R_g \tag{6.1}$$

$$\text{Reserve energy payment}: \ \rho_{R,g}^{\mathrm{Energy}} * \mathrm{RE}_g \tag{6.2}$$

where:

$\rho_R^{\mathrm{Cap.}} =$ clearing price of reserve capacity:
$\rho_R^{\mathrm{Cap.}} =$ lagrangian coefficient of the reserve capacity constraint
$\rho_{R,g}^{\mathrm{Energy}} =$ Reserve's energy bid offer of the winner generation unit g

X times of the energy bid of each market player is added to its proposed capacity price to determine the cost function for purchasing capacity, which will increase the market prices; thus this added amount will be deducted at payments to neutralize the effect of increased prices. Costs related to the used energy are also considered as previous.

The combination of each winner participant's bids $\left(\mathrm{CB}_{R,g}^{\mathrm{Cap}} + X * \mathrm{CB}_{R,g}^{\mathrm{Energy}}\right)$ must had been less than the market price $\left(\rho_R^{\mathrm{Cap.}}\right)$; therefore, the paying price to him will be more than its bid for selling capacity $\left(\mathrm{CB}_{R,g}^{\mathrm{Cap}} \leqslant \left(\rho_R^{\mathrm{Cap.}} - X * \mathrm{CB}_{R,g}^{\mathrm{Energy}}\right)\right)$. The energy related payments are based on the energy bids. Thus both payments to a winner satisfy its offered prices.

Defining the X is the crucial point in this method. A recursive solution approach is used for determining X in Ref. [1], so that X increases from 0 to 1 by step size of 0.01 in each iteration and the capacity price is obtained from minimizing the total operation cost; a table is established which represents the total operation cost of the system for different values of X versus the applied amount of energy. And then the total costs in case of using the conventional method are compared with the case that energy bids are taken into account in the objective of ISO. Due to explicit dependency of the recursive solution method to the amount of applied energy, it can only be implemented for the past hours that the amount of applied energy of reserves are known and will not be applicable for ahead hours. However, the effects of considering the combination of bids are cleared well.

In the following, it will be presented that the amount of applied energy is not the only effective factor on X and a model for assigning X will be introduced and evaluated, then the whole algorithm is assessed.

Proposed algorithm for determining the combination of energy bids and capacity bids for optimal market operation

X is input of the ISO's problem but it will not be calculable before the end of operation time, thus determining X for next hours requires a forecasting process. Because of the complexity of the required forecasting problem, an ANN based method is applied in this paper to approximate the functioning of the system based

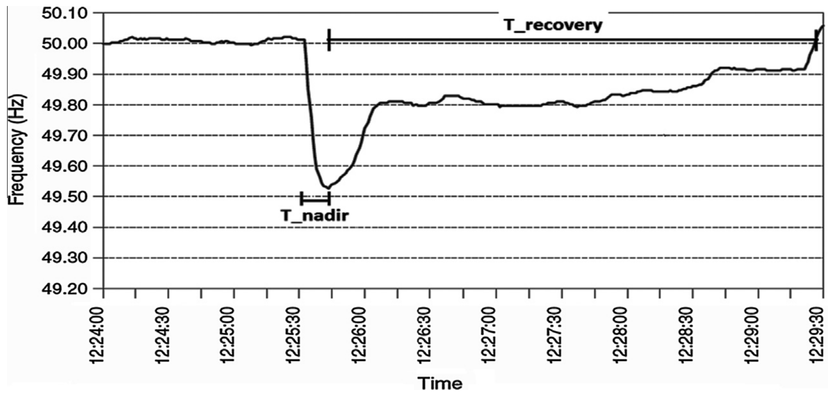

Fig. 2. Frequency deviations during generation outage at England power system.

on its nature using the historical data; error of this estimation and its effects on equilibrium point are evaluated. After forecasting the *X*, the ISO's problem should be solved to attain the equilibrium point. The following proposed algorithm describes the direction of information flow and decision-making subsequence's in an ASM to complete resolve of the problem, step by step:

(1) Receiving the bids and constraints of market participants for the next time interval.
(2) Receiving the historical data of market.
(3) Data preprocessing for providing the training and evaluation samples:
  (a) Calculating the *X* for previous hours whereby recursive method.
  (b) Substitution of some massive inputs of ANN with their statistical criteria.
(4) Feature selection: Sensitivity analysis and determining the effective inputs on *X*.
(5) Architecting the artificial neural network:
  (a) Determine the structure of the neural network layers and neurons.
  (b) Training a neural network involves determining the weights and excitation functions.
  (c) Evaluation of the ANN.
(6) Implementation of neural networks to forecast *X* for next hour.
(7) Implementing market-clearing problem using forecasted *X*.
(8) Declare price and payments related to capacity in reserve market.
(9) Real-time operation.
(10) Performing payments for energy.
(11) Determine the real *X* and performance evaluation.

Stages of the proposed solution

Data preprocessing and feature selection

In order to provide the training and evaluation samples, *X* will be determined for each past hour using the historical data whereby the described iterative method in Section 'Entrance of the energy bids into the market model'; *X* calculations will be performed once for each hour and is always utilizable. And for each time interval that market moves forward *X* should be calculated only for the last recent time period.

Sensitivity analysis of the historical data according to the algorithm of Fig. 3 is applied for feature selection. The ANN is trained and evaluated with and without each possible effective parameter in order to measure the importance of the feature by a ranking criterion. A high pass filter is used for selecting the inputs that their cancelation increases the forecasting mechanism error to higher than a threshold [21]. This step will be done once at the beginning of using the proposed method in the market and then it can be deleted from the algorithm.

Filtering threshold of this algorithm should be set less than maximum acceptable error of forecasting process, in this study it is assumed to be 4 percent, selected features are:

(1) Amount of required reserve capacity that is determined by ISO.
(2) Bids for capacity.
(3) Bids for energy.
(4) Participants' offered capacity.
(5) The amount of utilized reserve.
(6) Congestion occurrence in transmission lines, which is forecastable in a very good accuracy with respect to the load forecasting techniques and system condition.

Implementing the market participants' offers for capacity and energy causes a significant increase in the number of inputs. Thus four statistical criteria including minimum, maximum, average and variance for each one of the capacity bids, energy bids, and also for the amount of offered capacity are taken into account which reduces the total number of relevant inputs to 12. In this paper maximum and minimum of the offered reserve $\left(R_g^{\min}, R_g^{\max}\right)$ are assumed to be the same, so the offered capacity has only 4 statistical areas in case that these bounds are different there will be 4 more statistical criteria for the relevant inputs.

High sensitivity of *X* to applied energy of reserves represents a strict dependency to the amount of applied energy which is not known for upcoming hours until passing operation time. Thus it must be substituted by the criteria with the same influence and sufficient accuracy in functioning. There are two factors that lead to difference between production and consumption which result in reserve utilization: 1. Load forecast error, 2. in case of contingency. The load forecast error involves two components of the load fluctuations and the regular and periodic changes of load in each time period; each reserve provider should be paid for its total generated energy which is produced to compensate this error [2]. Energy of periodic errors and the total load fluctuations energy during an hour, which are dependent on the nature of system loads, are estimable; as the ISO determines their probability to purchase the required capacity for responding the worst possible condition. In case of discrepancy between generation and consumption, reserves will be called in percentages by system operator, and if the difference is large, i.e. if it is brought by an event, it will lead to implementation of full reserve capacity to avoid frequency droop. In this model, mathematical expectation

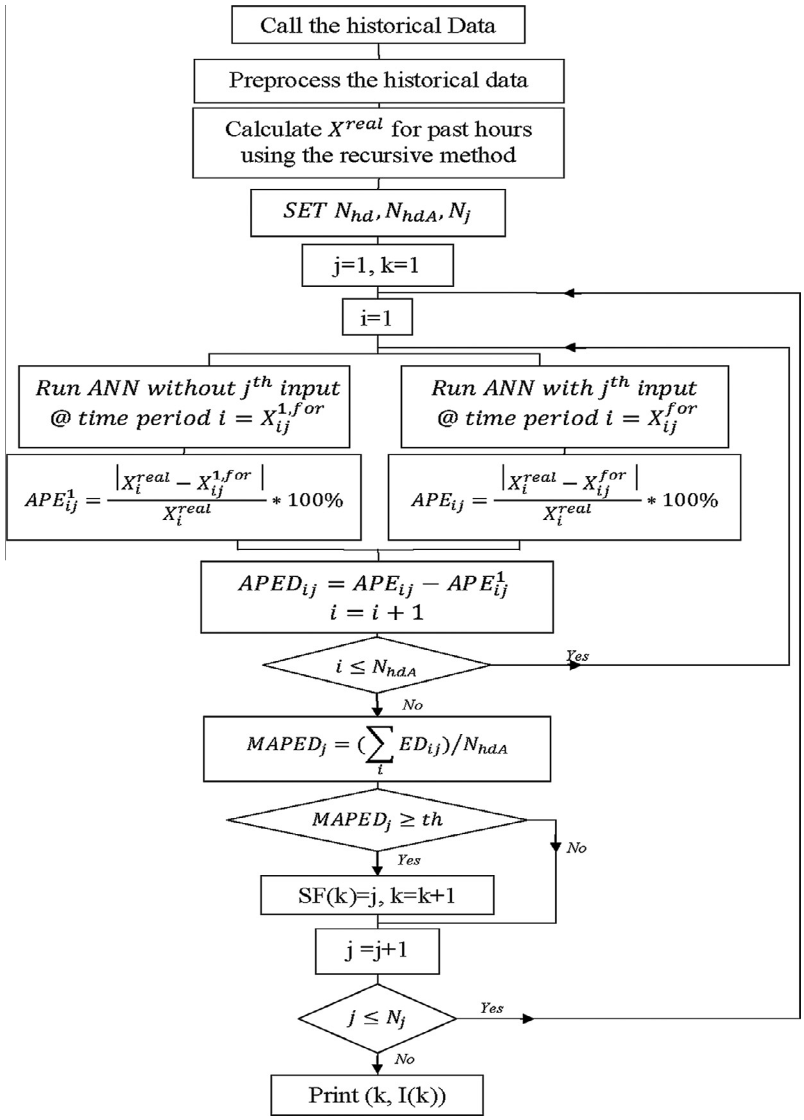

Fig. 3. Block diagram of feature selection algorithm.

of implementation of the reserve is considered as the alternative input which refers to the applied amount of energy and the effects of this substitution will be evaluated in case study.

Some features might not be selected as inputs to the proposed forecasting method still they implicitly and strictly affect it; load level is not an input to the implemented ANN, still amount of required reserve capacity, congestion indicator and amount of utilized reserve properly reflect its effect. Proposed offers of reserve providers and the amount of applied energy of reserves are also inputs of the ANN; by training the ANN using the data of similar days, it learns to estimate the effect of number of in service units and their characteristics.

Artificial neural network structuring, training and evaluation

Time periods are classified based on congestion occurrence and for each class a feed forward back propagation structure with a hidden layer is used in order to forecast the amount of X. There are 15 inputs; including 12 inputs for received offers from market participants, 1 for congestion status, 1 input is referring to the required capacity and the last input is for the mathematical expectation of load forecast error. In the hours with congestion on transmission lines, the number of inputs of required reserve capacity and load forecast error will be increased depending on system zoning. There is a neuron in the output layer for X. One hidden layer is used since it is proved that one hidden layer is enough for ANN to simulate any complex nonlinear function [22]. The number of hidden layer's neurons is determined using cross validation method, and the number of training samples is determined to minimize the evaluation error and avoid overtraining; 30 days from the day before the forecast day and 20 days before and after forecast day in the previous year are used as the training samples. In order to consider the effects of time-variant factors in the market and system, the sliding window method is used for neural network training algorithm. Sigmoid-shaped excitation functions have been used in this paper. After training, the neural network response will be evaluated using validation sample. In order to determining the neural network error, the algorithm is frequently applied and Mean Absolute Percentage Error (MAPE) is calculated:

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_i^{\text{real}} - X_i^{\text{for}}|}{X_i^{\text{real}}} * 100\% \quad (7)$$

ISO steps for modeling and running the market

For each hour, after receiving participants' bids, the ISO has enough inputs to run neural network in order to forecast X. Thus the ISO estimates X and define the market problem with the combined price of capacity and energy for purchasing required capacity. After the real time, energy payments are performed, so all the proposed process is completed and the only remaining step will be the model evaluation.

Reserve should be purchased to guarantee the reliability and stability of the system in worst condition, still reserves' energy is mostly implemented to maintain the load deviations under system's normal condition [2–4]. Therefore, this paper develops the reserve market model for normal operation condition while preparations (constraints) are considered for worst contingency condition. X is forecasted from the market's historical data using the similar days with normal operation condition [22]; then, the model performance is also evaluated for contingency condition in Section 'Effect of contingency'.

Other assumptions

1. Bid of each market participant for reserve capacity is a constant or a step function with limited number of steps.
2. Bid of each market participant for reserve energy is a linear function.
3. Initial system operation data including forecasted load, congestion status and the results of system stability and reliability studies which define the operation requirements are provided.
4. It is assumed that load flow calculations regarding to power exchanges of power market are done and output data including bus voltages and power flow of transmission lines are available to be used as the initial point of the power flow in the ASM, [17].
5. The ISO problem which is a nonlinear optimization is solved by Lagrange method.

Numerical results

A modified IEEE 24 bus reliability test system is applied to illustrate the proposed solution method, Fig. 4. Generation units data is as Table 2, Refs. [11,19].

ANN training and evaluation

Training and evaluation of the artificial neural network is done by the ISO's approach. Step by step of the procedure is as follows.

Randomly, it is assumed that the market is going to be run for the hour 17 of Tuesday of 30th week. By the ISO's calculations, the amount of required capacity is 91.31 MW and there will be congestion on some of transmission lines. Preprocessing of

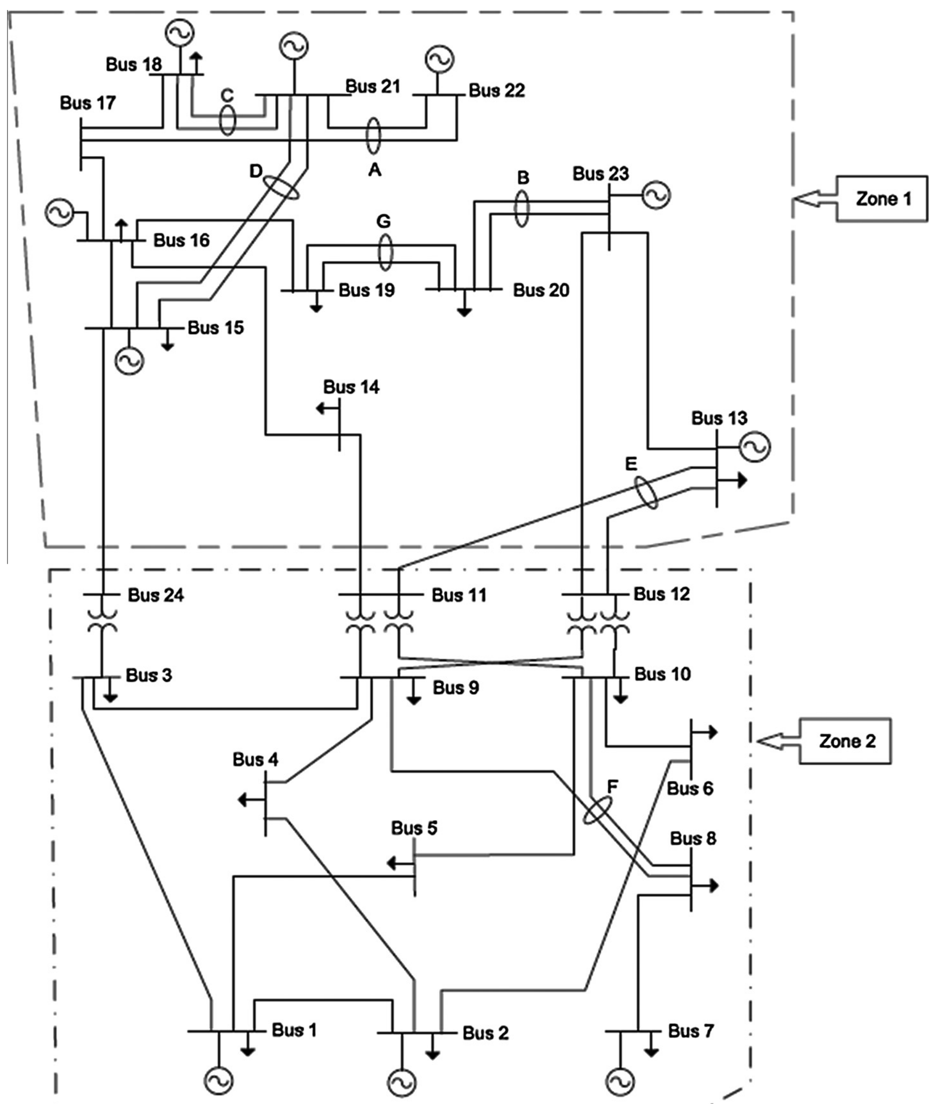

Fig. 4. IEEE 24 bus reliability test system.

Table 2
Generation units' data.

Unit name	Bus No.	P_i^{min} (MW)	P_i^{max} (MW)	Capacity for frequency response service (MW/min)
G1, G2	1	15.8	20	2
G3, G4	1	15.2	76	7.6
G5, G6	2	15.8	20	2
G7, G8	2	15.2	76	7.6
G9, G10, G11	7	25	100	10
G12, G13, G14	13	68.95	197	19.7
G15–G19	15	2.4	12	1.2
G20	15	54.25	155	15.5
G21	16	54.25	155	15.5
G22	18	100	400	40
G23	21	100	400	40
G24, G25	23	54.25	155	15.5
G26	23	140	350	35

historical data in order to obtaining the best X for training samples is the first step. 30 past hours from the target day and also 20 days before and 20 days after the target day at the previous year are considered as the similar days. Table 3 is the obtained Xs for the 30 past hours.

In this hour which the system is divided to two zones, Fig. 4, number of neurons of hidden layer is 9 which is obtained using cross validation of ANN results. The ANN is trained and evaluated as follows.

Forecasted coefficient X for evaluation sample is 0.268 which has been rounded to 0.27 while its real value is 0.28. ISO's purchased capacity from each zone and clearing prices for real X, forecasted X and with conventional methods ($X = 0$) are represented at Table 4. Absolute forecast error is 4.04%.

Note, system conditions are the same for all three cases; i.e. transmission lines constraint related to the lines available capacity is the determiner parameter for different zones to access to the resource of other zones of the system (3), so the amount of purchased capacity of each zone is remained the same.

In this hour, 67.75 MW of the purchased capacity is called to generation and payments are as shown Table 5.

Meanwhile system operation cost without considering energy bids is $ 1669.8, it would be $ 403.8 lower using proposed method which is 24.4 percent reduction. If the real X was accessible, it would be a bit less ($ 434.0 which is 25.9%) so the proposed algorithm error is 1.8%.

Proposed model evaluation

Evaluation of the model requires analyzing its performance over high number of executions. Therefore, the same procedure as the evaluation procedure of Section 'ANN training and evaluation' has been applied for 100 different hours and the model is evaluated using the outputs. The results of 20 randomly selected of these samples are presented in Tables 6 and 7 which are categorized based on congestion according to the neural network classifications.

Hours with transmission congestion

In case of congestion on transmission lines, the system breaks into two zones. Results of the provided model in comparison with conventional method are shown in Table 6. MAPE of forecasted is 2.04% and the system cost would be 1.3% lower if the real X could be exactly forecasted which is not possible. However the presented algorithm leads to 23.1% reduction in total payments.

The step size of recursive algorithm for providing the training samples is 0.01, thus the precision of forecasted X is about two digits and the third digit is rounded which sometimes results to disappearing the error, conversely, sometimes the error is increased. Totally, the effect of rounding credibly assumed neutral.

Hours without congestion in transmission lines

Number of neurons of hidden layer is obtained 6 for the optimum functioning of the ANN. Implementing the provided model, in this class total payment went down 7.9% and if the real X was available, reduction in costs would be 2.7% more. MAPE of the forecasting method is 4.3%.

Because of accessibility to all generation units from each point of the system in this class, clearing prices are less than the class with congestion on transmission lines. Graph in Fig. 5 represents the suggested model behavior at different hours versus X. Conventional method is the $X = 0$ which do not takes the energy bids into account, increasing in X reduces the operation costs till the lowest amount then it start to raise again. Due to the different systems' conditions and variation in market rules around the world and also the type of bid functions, the graph shape will varies for each market but the ascending–descending trend remains the same.

Effects of forecast error

Finding a solution in order to forecast the X is the major of provided model. Error of each block of the algorithm affects the model accuracy, graph in Fig. 6 represents the area of variation in total required payment versus X. Minimum of the trend is reached in $X = 0.35$, application of X between 0.01 and 0.69 leads to economic

Table 4
Amount and price pairs resulted in different methods for evaluation sample.

State	Zone 1		Zone 2	
	Purchased cap.	Zonal clearing price	Purchased cap.	Zonal clearing price
Considering energy bids, real X	42.68	13.74	48.63	4.95
Considering energy bids, forecasted X	42.68	13.42	48.63	4.87
Without considering energy bids	42.68	7.88	48.63	2.48

Table 5
Payments in detail.

State	Total payment for capacity $	Total payment for energy $	Total operation cost $
Considering energy bids, real X	483.46	752.36	1235.8
Considering energy bids, forecasted X	447.44	818.43	1266.0

Table 3
X for 30 past hours obtained from market history data whereby recursive method.

Hour	X for 30 past hours														
1–15	0.28	0.36	0.30	0.39	0.27	0.28	0.36	0.37	0.29	0.26	0.36	0.39	0.31	0.37	0.37
16–30	0.37	0.30	0.27	0.36	0.36	0.37	0.29	0.34	0.27	0.30	0.29	0.33	0.35	0.28	0.38

Table 6
Results of proposed model in comparison with conventional method at hours with congestion on transmission lines.

Row	State	Zone 1		Zone 2		Total operation cost $	Operation cost without considering energy bids $
		Purchased cap.	Zonal clearing price	Purchased cap.	Zonal clearing price		
1	RX = 0.350	48.18	15.30	54.91	5.53	1421.0	1792.6
	FX = 0.353	48.18	15.30	54.91	5.53	1421.0	
2	RX = 0.430	49.19	17.14	56.05	6.17	1549.4	1923.9
	FX = 0.416	49.19	16.85	56.05	6.09	1563.5	
3	RX = 0.330	50.19	14.91	57.10	5.40	1514.1	1961.2
	FX = 0.324	50.19	14.61	57.10	5.31	1548.9	
4	RX = 0.330	46.67	15.07	53.19	5.40	1703.7	2317.4
	FX = 0.305	46.67	14.20	53.19	5.16	1788.3	
5	RX = 0.400	44.57	16.46	50.80	5.92	1530.3	2006.1
	FX = 0.402	44.57	16.46	50.80	5.92	1530.3	
6	RX = 0.270	45.52	13.54	51.87	4.89	1304.1	1733.5
	FX = 0.271	45.52	13.54	51.87	4.89	1304.1	
7	RX = 0.290	46.47	14.02	52.96	5.05	1395.7	1978.7
	FX = 0.289	46.47	14.02	52.96	5.05	1395.7	
8	RX = 0.320	47.42	14.65	54.04	5.29	1407.0	1853.1
	FX = 0.322	47.42	14.65	54.04	5.29	1407.0	
9	RX = 0.420	44.10	16.92	50.26	6.08	1568.9	2094.5
	FX = 0.412	44.10	16.62	50.26	6.00	1602.9	
10	RX = 0.410	47.08	16.62	53.65	5.97	1405.7	1773.0
	FX = 0.394	47.08	16.03	53.65	5.81	1444.8	
11	RX = 0.320	48.08	14.71	54.79	5.29	1478.7	2000.2
	FX = 0.317	48.08	14.71	54.79	5.29	1478.7	
12	RX = 0.360	49.09	15.69	55.94	5.62	1687.8	2224.9
	FX = 0.346	49.09	15.07	55.94	5.46	1754.3	
13	RX = 0.300	50.08	14.35	57.07	5.15	1564.3	2190.6
	FX = 0.294	50.08	14.02	57.07	5.08	1581.0	
14	RX = 0.290	46.58	14.04	53.08	5.08	1523.5	1943.1
	FX = 0.296	46.58	14.36	53.08	5.16	1542.4	
15	RX = 0.370	45.53	15.82	51.88	5.68	1471.6	1924.5
	FX = 0.363	45.53	15.51	51.88	5.60	1473.6	

RX = considering energy bids, real *X*. FX = considering energy bids, forecasted *X*.

Table 7
Results of proposed model in comparison with conventional method at hours without congestion on transmission lines.

Row	State	Purchased cap.	Market clearing price	Total operation cost $	Operation cost without considering energy bids $
16	RX = 0.09	88.33	5.39	1000.9	1153.0
	FX = 0.096	88.33	5.80	1029.1	
17	RX = 0.12	90.21	6.02	1119.4	12552.2
	FX = 0.113	90.21	5.38	1176.7	
18	RX = 0.10	92.09	5.40	1008.2	1044.7
	FX = 0.105	92.09	5.76	1019.8	
19	RX = 0.13	93.96	6.13	1209.5	1411.4
	FX = 0.124	93.96	6.02	1261.7	
20	RX = 0.08	87.39	5.22	915.8	953.2
	FX = 0.83	87.39	5.22	915.8	

RX = considering energy bids, real *X*. FX = considering energy bids, forecasted *X*.

benefits, the closer forecast results in less operation cost. Here, considering the expected error of the solution method, 2.04%, it is justified to reconsider the existing methods.

Effect of contingency

In case of events in a power system, the frequency response service providers are the vanguards to keep the system frequency up until the next supports get involve; their produced energy would increase up to their full available capacity to stop frequency falling down below the acceptable margins. Although the provided model clears the market considering the *X* that is forecasted based on mathematical expectation of applied energy which maintains the load trace service and in case of contingency condition more energy would be required, the rational expectation is a better functioning of the suggested model than models which totally ignore the energy bids in their optimization procedure.

Table 8 presents a comparison of effects of increase in amount of applied energy between different amounts of *X* at a passed hour. In real time operation 60.54% of purchased capacity had been applied at this hour. The real *X* is 0.25 and the forecasted *X* is 0.26.

If 100% of capacity were called to generate, total payment would grow $ 653.27 using the implemented model meanwhile this growth would be $ 1249.4 for conventional method. As it was anticipated, provided algorithm has a better functioning than conventional model.

Note, if the real *X* was applied, the increase in system's operation cost would be a little more than applying the forecasted *X* and it is because of the forecast error, which in this case leaded to a larger forecasted *X* than the real one; so when the energy usage goes up, using forecasted *X* had a better action. The point is that this could be inverse and this amount of error seems inevitable.

The graph in Fig. 7 is the system costs versus applied energy. $X = 1$ is the explicit summation of energy and capacity bids.

Amount of capacity cost at the suggested model is almost same as conventional method, because *X* times of energy bid of each winner participant is reduced from market price at the capacity payment procedure which stops the costs go much upper, therefore the market players with the lower energy bids receive their capacity revenue at a higher price; also this part of frequency response service providers' income is independent from amount of their produced energy so the relevant trend on the graph is constant.

Energy trends start at zero and goes up by increasing in the amount of applied energy. *X* and rate of growth in energy cost are inversely related; therefor by increasing in the amount of

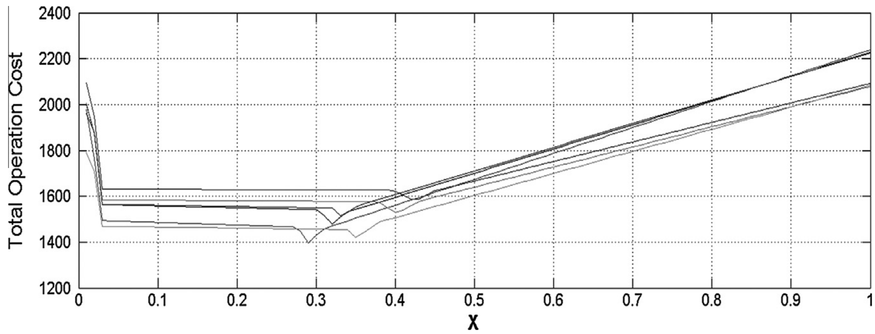

Fig. 5. Total operation cost trend for different hours versus *X*.

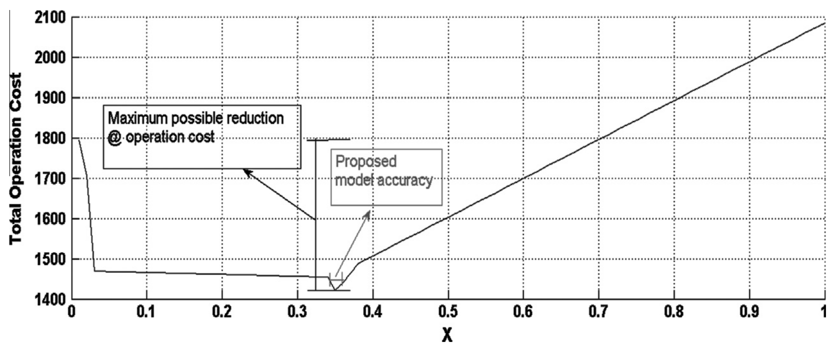

Fig. 6. Total operation cost versus *X*.

Table 8
Operation cost in case PE% of capacity were called to generate $.

State	PE = 60.54% (normal operation)	PE = 70%	PE = 80%	PE = 90%	PE = 100%
Conventional methods, $X = 0$	1003.3	1299.3	1614.7	1932.5	2252.7
Proposed algorithm, Real X	841.5	1021.7	1213.4	1406.5	1600.9
Proposed algorithm, Forecasted X	853.8	955.4	1122.8	1314.2	1507.1

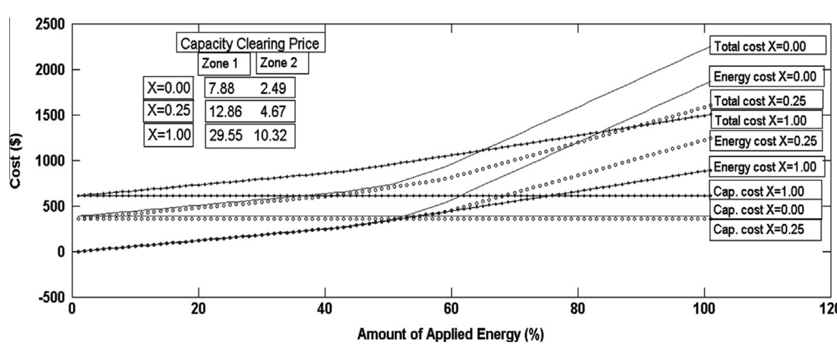

Fig. 7. Operation costs in detail for an hour versus implemented energy.

applied energy total cost of implemented algorithm will be lower than conventional model.

If the objective of ISO were defined as minimization of the direct summation of capacity and energy bids ($X = 1$), applying higher amounts of the purchased capacity was much more cost effective; the effect of offered energy prices is so much that at the lower amounts of applied energy the total cost of this case is considerably over the others. At the more reserve energy usage the lower energy price comes over and this method is more economical (If ISO has used more than 86% of the purchased capacity this case had a better economic efficiency).

Conclusion

Neglecting the energy cost in conventional ASM models deviates the ISO's decisions from the optimal conditions, leading to additional costs for providing system operation requirements. In this paper, an applicable method is proposed for an ancillary service market for taking the energy bids of competitors into account to achieve the optimum performance of the market regarding to the technical requirements of system; at first, an artificial neural network is implemented by the ISO to forecast the effect of offered energy prices on the equilibrium point, then the results are applied to modify the ISO's problem to make it closer to what comes to happen in operation time, and in the final step, the functioning of the model is compared with the conventional market models which illustrate the necessity of considering energy costs of reserves in market equations. Effects of contingency occurrence are studied as well.

Synchronicity of reserves' markets and in a more general approach considering simultaneous power market can be noticed in future researches.

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