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Energy Scheduling in Power Market under Stochastic Dependence Structure

Mehdi Farhadkhani[1]

Electricity Economics & Energy Research Group, Niroo Research Institute (NRI),Tehran, Iran

Abstract

Since the emergence of power market, the target of power generating utilities has mainly switched from cost minimization to revenue maximization. They dispatch their power energy generation units in the uncertain environment of power market. As a result, multi-stage stochastic programming has been applied widely by many power generating agents as a suitable tool for dealing with self-scheduling strategies under uncertainty. However, dependence structure between stochastic variables has been almost ignored in the literature. Copula function is a new concept in the probability and statistics field which has the capability to represent the dependence structure among stochastic variables. However, Copula function has recently taken into account in power system studies by some articles. In this article, self-scheduling strategy of a generation utility owning thermal units is investigated while the dependence structure among stochastic load and market price variables is taking into account. We assume that the generation utility is a price-taker agent in a power market, and it also has to meet the load of a specific region as a retailer. The results indicates that as the stochastic dependence structure among load and price variables is considered in modeling load and price scenarios, the output of unit commitment problem changes so that the revenue of generation utility increases.

Keywords: Unit Commitment; Stochastic Dependence Structure; Multistage Stochastic Programming; Scenario Tree Construction; Copula Function.

1. Introduction

Energy scheduling is the main task of power generation companies and system operators to take profit from energy trade in power market, reduce generation costs, and maintain power system security. Energy scheduling is mainly conducted through unit commitment, unit on/off scheduling. Hence, unit commitment decisions are significant to maintain reliability and cost efficiency in the power system as a whole. In general, the goal of unit commitment problem is to find a unit on/off schedule that minimizes the commitment and dispatch costs of meeting the forecasted system load, taking into account various physical, inter-temporal constraints for generating resources, transmission, and system reliability requirements [1].

From a system operator view, in the event that the actual system condition obviously deviates from the expected condition, the system operator needs to take corrective actions such as committing expensive fast-start generators, voltage reduction, or load shedding in emergency situations to maintain system security [1]. In the other hand, a generation utility tries to reduce the cost and maximize the revenues of power energy generation by producing energy in peak energy price hours.

Hence, this energy scheduling model is a typically large-scale stochastic optimization decision making model which takes into account stochastic input parameters such as the demand for replacement reserves, wind and solar power energy production forecasts, load and market price forecasts. The model evaluates optimal unit commitment and economic dispatch at hourly time-resolution and minimizes the expected value of production costs of the system that comprises fuel cost, start-up cost, and variable operation and maintenance cost [2].

However, optimal unit commitment in power market is an intricate decision making problem since there are several random and uncertain influential factors in power market that affect optimal dispatching of generation units. Unit commitment strategies in high uncertain environment have been under specific attention in recent years. With the uncertainty that is presented in random variables such as electricity demand, market-clearing price, penetrating renewable resources of energy which are volatile, and uncertainties associated with the load forecast error, changes of system interchange schedules, generator's failure to follow dispatch signals, and unexpected transmission and generation outages, it is of special importance to plan the system in an efficient and robust way in order to reach several uncertain potential outcomes [1,2].Therefore, modeling random variables has a vital role in energy scheduling since. If we could not forecast influential random variables in energy scheduling accurately, then we will make decisions on unit commitment based on improper information; this could result in fatal economic and security decisions for a generation company (Genco) and power system.

Many authors investigated effects of stochastic variables in unit commitment of Gencos from different views and aspects. There are many articles about optimal scheduling of hydro-electric power generation and modeling random water inflow and price of the market in order to optimize profits of hydro Gencos [3-8]. Furthermore, a lot of study have been conducted on the effects of operation of renewable energy especially wind and solar energy in unit commitments [9-21]. Some other authors argue stochastic unit commitment in general in power market [22,23].

However, less attention is paid to modeling dependence structure of stochastic variables in unit commitment decision making process, or dependence structure has been only limited to linear correlation between random variables. While stochastic dependence structure is not only restricted to linear correlation. Extensive research and studies have been conducted in this subject in finance and risk analysis of financial markets. It is shown that dependence structure among random variables is more complicated than linear correlation. This could change the results of quantitative relations and equation drastically. There are few stochastic unit commitment studies taking into account nonlinear stochastic dependence structure between random factors [e.g., 18,24]

Then, in this paper, we investigate energy scheduling strategy of a Genco taking into account stochastic dependence structure between random variables, in this case load and market-clearing price. We assume the Genco acts as both a retailer and a power generator such that it must meet the electricity load of a specific region. For this aim, we model nonlinear stochastic dependence structure among load and power market price by a copula function. In the second section, we describe how to generate load and price scenarios. In the next section, stochastic dependence structure among load and price is modeled by means of copula function. In order to reduce the curse of dimensionality of optimization problem, the random scenarios (load and price) are simulated in section 4. Hence, scenario reduction methodology is applied to construct two load-price scenarios considering two different dependence structures between random variables, linear and copula. Then by defining a measure, we will show scenario tree made taking into account copula dependence structure among random variables is better than the one made by linear dependence structure. In the final section, we will solve unit commitment problem applying each scenario tree and show that considering dependence structure between random variables will result in a better unit commitment solution.

2. Scenario Generation

A) Load and Price Simulation

A scenario is a time series of random variable/variables. Several different methods to generate scenarios are represented and proposed so far. These methods include a wide range of statistical methods that aim to generate abundant amount of samples in order to form different stochastic scenarios so that stochastic pattern of our random variables are simulated.

In general, we need to have enough knowledge and perception about the stochastic behavior of all random variables to cope with stochastic problems. Problems are categorized to different levels according to the information they give about their random patterns [25]; they represent all the needed information of their stochastic variables, general random behaviors (their parametric probability distribution function), random samples, or even less information [25].

In our case study, historical samples of hourly load and price of Iran power market are available, 75 samples from each hour for each load and price. According to the central limit theorem, probability distribution of samples of each time stage (hour) could be highly approximated by normal distribution. Then, samples are fitted to normal distribution and corresponding parameters (mean and standard deviation) are estimated.

Monte Carlo simulating method is applied to simulate 100 samples for each variable in each time step. To do so, having normal probability distribution of samples, cumulative distribution functions of samples are drawn. Then, [0,1] distance is divided to 100 equal parts; next a random sample is randomly taken from each part. In this way, abundant random samples are taken from different parts of the probability distribution function; more samples are taken from more probable distances.

Applying above process, 100 load scenarios and 100 price scenarios are generated. Remember two-variate load-price scenarios are the input of our unit commitment problem. Load and price samples of each time step should form two-variable samples. The question is which two load-price samples sit aside each other and what the correct arrangement of load and price samples is to form two-variate samples. This is the question which will be answered in the next section.

B) Stochastic Dependence Structure Modeling

Measuring the dependence structure among random variables is often represented by linear correlation whereas in this way great part of information related to the stochastic dependence structure might be neglected. Pearson's correlation method represents dependence structure of random variables better than linear correlation since it assumes the elliptical shape of normal distribution in applications. The research in this subject resulted to take a special attention on copula function.

The correlation between random variables or samples is measured by the Copula concept. Recently, much attention is being paid to copula concept in statistical modeling and simulation problems especially in Finance. Copula function is a suitable means to represent dependence structure of random variables by defining a mapping from cumulative distribution of joint distribution of random variables to cumulative distributions of each separate marginal distribution.

Copula function is a function that links (couples) the univariate marginal distributions to the joint distribution. Copulas provide a way to generate distribution functions that model the correlated multivariate processes and describe the dependence structure between the components. The cumulative distribution function of a vector of random variables can be expressed in terms of marginal distribution functions of each component and a copula function. In contrast to the correlation coefficient which measures co-variations up to the second order, copula functions captures the complete/perfect dependence structure [26,27].

This capability makes the copula function as a very effective means for modeling and simulation of dependent random variables. There are several different kinds of copula functions that Gaussian Copula is the most common one.

In this paper, d-dimensional Gaussian Copula was employed to derive dependence structure between load and price samples according to the following algorithm [28]:

- Simulate: $X \sim N_d\ (0,R)$
- Set: $U=(\ \Phi(X_1)\ ,\ \dots\ ,\ \Phi(X_d)\ )$

Where $N_d(0,R)$ is the multivariate Gaussian distribution with expectation 0, correlation matrix R between load and price samples, d is equal to 2, and Φ denotes the distribution function of a standard univariate Gaussian distribution.

Having linear correlation between historical load and price data, we simulated Gaussian copula for load and price variables. Fig. 1 illustrates histograms of simulated load-price variables of two time stages taking into account stochastic dependence structure as linear correlation among load and price variables and as copula function of these random variables. It is obvious that the samples drawn from linear and copula dependence structure models are generally alike. However, there are differences in pattern of samples especially in tails of the samples.

3. Electricity Market Price-Load Scenario Tree Generation

After dependence structure simulation, scenarios are generated to form two scenario fans. Determining optimum value of our objective function through the scenario fan is a large-scale and, in most real cases, an impractical problem. The number of nodes of each scenario fans is so large that solving the optimization problem is almost intractable or impractical; the number of scenarios of each scenario fan needs to be reduced. Hence, the clustering methods are applied to generate multistage scenario tree from the set of individual scenarios by bundling scenarios based on cluster analysis. For instance K-means clustering approach can be applied in order to capture the inter-stage dependencies in scenarios [28]. This method is implied to make a scenario tree for sampled data of discount bond yields [28]. Probability clustering by appropriate probability metric is another approach to generate scenario tree that has been employed in some stochastic power management models [29,30,31]. In this approach, both scenarios and total nodes of scenarios are reduced so that the probability distance between an initial scenario fan and its scenario tree takes a minimum value. In this approach, forward and backward algorithms are proposed to generate a scenario tree from the initial scenario fan. These algorithms are based on a stage-by-stage process in which deleted candidates or remaining candidates are selected according to their probability distances from other nodes. This process terminates when all candidates' probability distances are equal to or more than a predetermined tolerance. Ultimately two sets of nodes or points including remaining and deleted nodes are formed. Theses algorithms are described in detail in [31,32].

In forward scenario tree algorithm, scenarios are clustered in a forward way, starting from first stage to the last one. In this paper, forward scenario reduction is applied to construct scenario tree. Moreover, Error Tolerances of each step is the same formula as Heitsch and Römisch applied in their article [33].

In this way, we first estimated normal probability distribution, linear correlation, and the corresponding Gaussian copula according to 75 historical samples from load and price of Iran power market in each daily hour. Then, we simulated two series of load-price bi-variate samples for each daily hour, one by the use of Monte-Carlo simulation method from estimated normal probability distribution and linear correlation (that is, the corresponding estimated Gaussian probability distribution), and the other one by simulating estimated Gaussian copula. Hence, two scenario fans, each containing 100 scenarios are generated; one by considering linear correlation (we call it linear scenario fan), and another one by considering copula dependence structure among load and price variables. Copula dependence structure scenarios are made by simulating Gaussian copula of between historical load and price in each hour. Hereafter, we call the former scenario structure, linear scenario fan and the latter, copula scenario fan.

In the next step, two scenario trees are generated by employing forward scenario tree construction method, considering the same tolerance variation for both of them. This resulted to two scenario trees with 47 and 46 scenarios respectively from linear scenario fan and copula scenario tree. Hereafter, we call the former, Linear Scenario Tree (LST) and the latter, Copula Scenario Tree (CST). The numbers of nodes in LST and CST were reduced to 874 and 808 nodes respectively from 2400 initial node embedded in their associated scenario fans. Figs 2(a) and 2(b) illustrate LST and copula CST respectively.

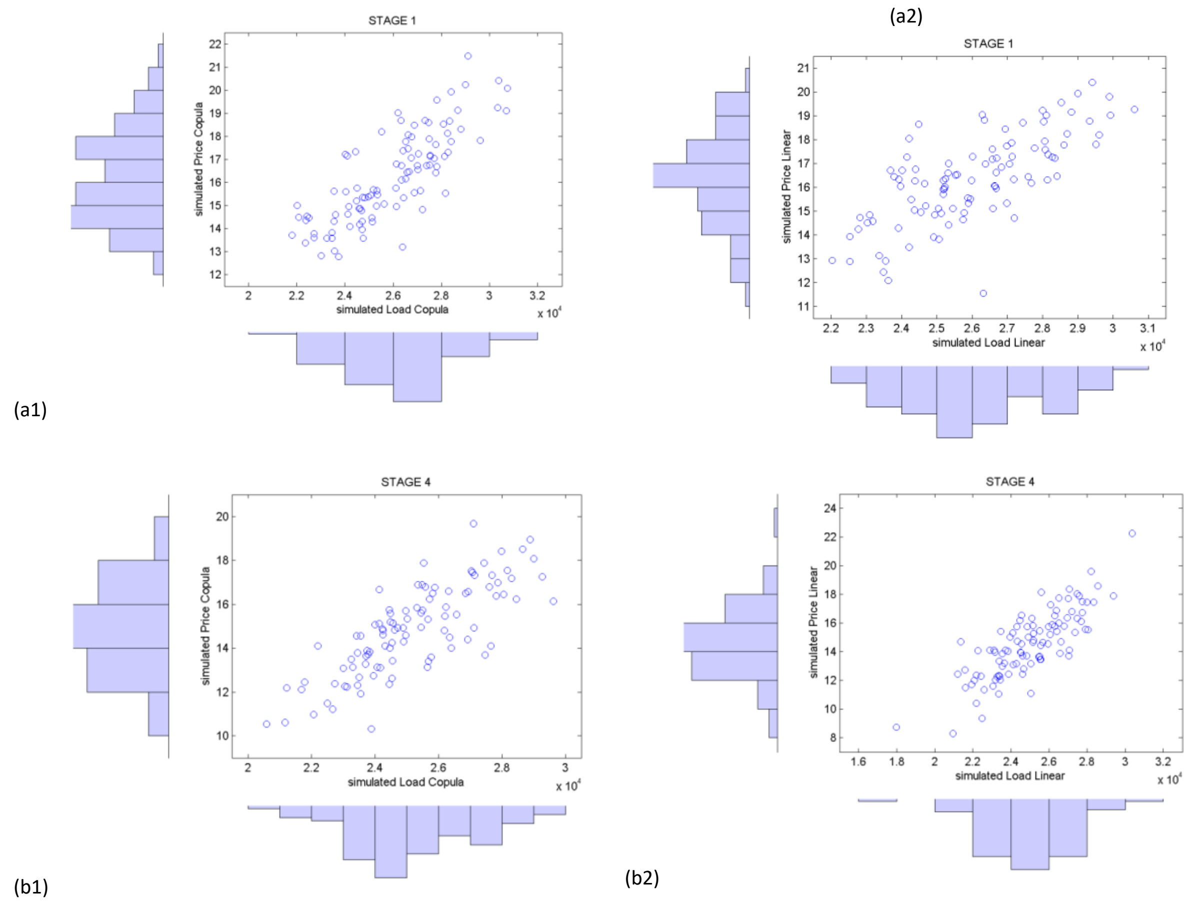
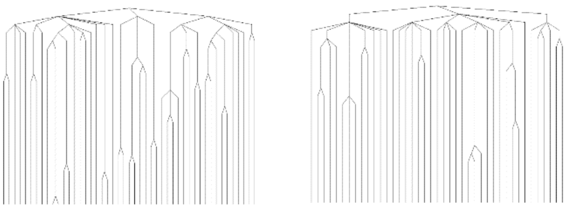


Fig. 1. Comparison of histograms of simulated load-price variables of some of time stages incorporating linear dependence structure (left-side histograms) and copula dependence structure (right-side histograms). Histogram of samples in stage 1 and stage 4 is illustrated in (a1),(a2) and (b1),(b2).



(a) (b)

Fig. 2. (a) linear dependence structured scenario tree (LST) (b) copula dependence structured scenario tree (CST)

Here we present a measure introduced in [25] to compare scenario trees generated with different approaches. This measure, that we call it SCenario Tree Probability Distance Mean (SCTPDM), compares the distance of each scenario tree from its original scenario fan. Probability distances between a scenario tree and its original scenario fan can be evaluated by this measure. To gain the measure, probability distance of each scenario of a scenario tree from its scenario fan is determined and its mean is evaluated as our measure. For illustrating the probability distance of a scenario tree form its original scenario fan, its probability distribution of the distance is plotted. Probability distribution of this probability distance and mean value of that distance for two approaches show how close each scenario tree is from its scenario fan. We can express the mean of the probability distance of a scenario tree form its derived scenario fan mathematically as the following equation:

$$\mathrm{SCTPDM_i} = \mathrm{P_{s,j}}.\min_{j\epsilon \mathrm{SCFan}} \left\| \eta_s^i - \eta_s^j \right\|^r$$

Where SCTPDMi is the probability distance measure of the ith scenario of the scenario tree from its scenario fan, Ps,j is the probability of scenario ηi in stage s, ηis is the sth stage of ith scenario of scenario tree and ηjs is the sth stage of jth scenario of scenario fan of the scenario tree, || . ||r is r-norm function. Note that the result is the sum of the production of the probability of each node of a scenario of a scenario tree by the distance scenario ηi of the scenario fan.

According to SCTPDM, LST is farther from its scenario fan than CST according to probability distance measure.

Mean SCTPDMlinear=0.1062, Mean SCTPDMCopula= 0.0960.

Fig. 3 illustrates more details about SCTPDM of LST and CST. Blue curve indicates distribution probability plot of SCTPDM of scenarios of LST and the red curve shows that of CST. The range of SCTPDM of LST is about [0, 0.5141] while that range is almost [0.0517, 0.3611] for CST. As it is considered from the plots, SCTPDM of LST scenarios are highly farther than that of CST scenarios.

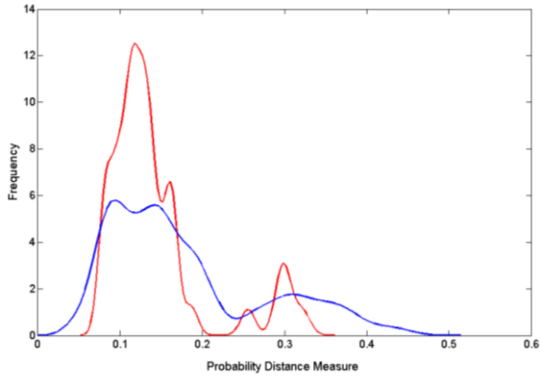


Fig. 3. Comparison of probability distance measures of Linear Scenario Tree (LST) and Copula Scenario Tree (CST)

4. Self Energy Scheduling Based on Stochastic Dependence Structure

In this section, it is shown that considering dependence structure might impact the energy scheduling of a Genco and consequently affects its revenue and profits. To show this, a case study of a Genco owning 10 thermal units is introduced. This model and its detail information are taken from [34]. It is assumed that the Genco acts as a retailer in power market. In better expression, it must meet the load of an area. It has two options: to buy power energy from market or to produce energy by its own units. The Genco's aim is to gain more profits considering meeting the load and reducing its generation costs. In order to achieve this target, it should decide when and how much electricity to produce by its units. Similarly, the optimal strategy for electricity retailer under uncertain environment is determined in more detail in [35]. However, our aim is to show that energy scheduling in an uncertain environment by considering perfect stochastic dependence structure between random variables result in more profits for the Genco or a power generation utility.

Bidding strategy of a Genco is believed to be based on its market price and demand forecasting [36]; therefore, these two stochastic variables are of special importance in self-energy scheduling of the Genco. Although fuel cost and Forced Outage Rates (FOR) of units are other influential factors that can affect self-scheduling of a Genco, we do not incorporate these factors in this study.

Self-energy scheduling of the Genco needs to apply Stochastic Programming approach. As stated before, load and price scenarios were simulated, reduced the dimensionality of the combinatorial optimization problem by constructing related scenario tree, and in this phase, the stochastic programming problem is solved by applying scenario trees. Expected profits of self-energy scheduling of the Genco is the solution of the problem. The results for both states, when considering copula dependence structure and linear dependence structure among load and price variables, are determined. The results are shown in tables 1 and 2.

Table.1.
Genco's units on-off scheduling considering linear dependence structure among load and price

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
U 1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
U 2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
U 3	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0	0
U 4	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0
U 5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
U 6	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U 7	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U 8	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U 9	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U 10	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table.1.
Genco's units on-off scheduling considering copula dependence structure among load and price

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
U 1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
U 2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
U 3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
U 4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
U 5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
U 6	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1	0	0	0	0
U 7	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
U 8	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
U 9	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
U 10	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0

As it is considered, green and red cells indicate an on-state of a power generation unit in a specific hour. Red cells indicate the states in which the results of the two stochastic dependence models are not the same; that is, while a unit in a specific hour is on in a model while at the same hour, that unit in the another model is scheduled to be off. It is obvious that the units are in on-state in more hours in the copula dependence structure model than in the linear dependence structure model.

The expected profits of the Genco in the two models are 1089858 and 1229800 for the Linear and Copula model, respectively.

As a result, the Genco prefers to generate more power in linear model than in copula model. While in the linear model the Genco prefers to buy power from electricity market than to generate by its own units. Moreover, the case in which the Genco considers copula model, it should expect to gain more profit than in linear model since the former model simulates price and demand dependence structure more accurately.

5. Conclusion

In this study, we showed how perfect stochastic dependence structure between random variables affects self-energy scheduling of a Genco. First of all, load and price scenarios of Iran power market were simulated by two approaches. In the first approach, linear dependence structure among load and price variables were incorporated in simulation process by taking into account linear correlation among historical load and price data. In the second approach, load and price scenarios were simulated by applying copula function of load and price. To do this, Gaussian copula function was simulated from available information of historical load and price data.

Due to the curse of dimensionality, load-price scenario trees of the original scenarios were constructed. In order to indicate that the scenario tree generated through copula based scenarios is a better scenario tree than that of linear dependence structured scenarios, a suitable measure, SCTPDM, was defined in aspect of the probability distance measure from their corresponding scenario trees and applied. It was shown that this measure is lower for CST than for LST.

Finally, stochastic programming problem of self-energy scheduling was solved for both CST and LST separately. As a result, on-off scheduling of units of the Genco was drawn for CST and LST models. It was concluded from the results that Genco tends to produce more power energy in CST model than in LST one. Moreover, expected profit of the Genco in CST model is more than in LST one.

Incorporating more influential random variables for self-energy scheduling is proposed for future research. Energy scheduling can also be extended to all power units in a power system considering security constraints. Of course, in this case, a system operator will schedule power units of the power system according to generation bids of Gencos and security of the whole power system. The aim of this energy scheduling would be mainly to maintain the security of the power system while reducing generation costs.

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