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Reliability based planning and operation planning of thermal-wind units

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Abstract

Today, the issue of planning and operation planning of thermal units (TUs) based on generation system reliability has become very important due to the restructuring process in power systems, load increment and distributed generation penetration on the demand side. This paper proposes a two-step approach to solve the aforementioned issue in the presence of wind farm renewable energy resources in the electricity market environment. In the first step, the optimal installation capacity of TUs is determined by the goal of providing annual peak load and being at the desired level of generation system risk using the loss of load probability analysis. Their economic dispatch and spinning reserve are determined in the second step. Expected energy not served is used for generation system reliability evaluation in the operation planning phase. Single contingencies of TUs are defined as system uncertainty. It is assumed that wind farm has constant capacity in the planning phase, and it generates active power (negative injection) as a function of wind speed at the installation region in the operation planning phase. Auto Recursive and Moving Average time series model is applied for wind speed estimation at different time intervals in the operation planning phase. The genetic algorithm has been used to solve this optimization problem. To validate the effectiveness of the proposed model, numerical studies and simulations are performed on the standard test generation system with 32 TUs and 1 wind farm. Finally, conceptual results have been expressed.

Keywords: thermal-wind units, operating reserve, generation system reliability, well-being analysis (WBA), auto recursive and moving average (ARMA)
2020 MSC: 74F05

1 Introduction

In the power system adequacy field, the reliability assessment of the generation system (HLI) is dedicated to meeting the network peak load demand at the long-term time interval in the planning phase and daily load demand at the short-term time interval in the operation phase. Power system operators are constantly faced with some issues such as sudden increases or decreases in load demand, forced outages of generating units, etc., which must be immediately thought of as a solution to ensure economic performance at an acceptable level of reliability. Operating reserves including spinning and non-spinning reserves, are often considered to face these uncertainties. In general, reserve determination methods are divided into two categories such as deterministic and probabilistic. The deterministic

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method determines the amount of operating reserve based on various criteria such as the percentage of system load or generation capacity, the largest unit or a combination of them. The basis of the probabilistic method for determining the operating reserve is the probability calculation of committed power generation to achieve the expected satisfaction during the lead time of the system. The process of evaluating the amount of operating reserve in the generation sector pays attention to the number and capacity of units participating in power generation and their ramp rate to respond to the power generation change when needed. Recently, a new method has been proposed for operating reserve evaluation using combining deterministic and probabilistic methods which is called well-being analysis (WBA). This method can show the operational situation of the power system with more details [12]. In the last decade, the use of renewable energy sources, especially wind energy, has been widely welcomed due to its economic benefits and positive environmental effects, but the variable nature of energy generation by these resources leads to a new challenge for power system operators. However, various solutions such as installing batteries and using more operating reserves have been suggested to overcome this problem. Due to the discussion importance, many studies have been done in this field up to now. In [11], the power system reliability in the presence of energy storage has been evaluated, and the Energy Storage System (ESS) capacity effect on the optimal amount of operating reserve is discussed. In [10], changing the reliability level at the demand side of the power system due to high penetration of Wind Turbines (WTs) capacity is investigated and a new probabilistic-based framework is introduced. In [17], Power systems adequacy analysis is evaluated in the presence of WTs and ESSs resources during operation planning time intervals. It is considered to thermal units (TUs) and batteries response rates and also WTs variable output power to model the expected energy not served. In [8], reliability evaluation in the short-term and medium-term time intervals of the operation planning process is considered about the high penetration capacity of WTs. To construct the reliability model, TUs, rapid-start gas turbines and WTs have been developed. In [16], the reliability evaluation of power systems under high penetration of WTs resources with the concept of the risk area. New modelling based on WBA is applied for the short-term scheduling of TUs and WTs resources, simultaneously. In [2] a risk-constrained model has been surveyed with the goal of the risk and operating costs minimization concerning various uncertainties such as load fluctuations, WTs output power variation and single contingencies related to TU's failure. In [14] a two-stage security constraint robust model for generation system hourly scheduling was suggested about uncertainties such as load demand fluctuations and WTs output power variation. Other research in [13] offered the Monte Carlo method for the reliability indices calculation of power systems in the presence of WTs, and in order to estimate the wind speed in the region, the ARMA time series model has been used. Other authors in [15], Penetration increment possibility of WTs has been investigated by real-time pricing in the electricity market and the participation level of the units are optimally determined. In [4], power system generation adequacy assessment has been noticed using WBA and changes in expected energy not served of customers are estimated based on peak load and probability of system placement in each system operation state as a function of WBA probability. A similar disquisition in [6] has considered the presence of WTs when WBA is applied for generation system adequacy analysis. Various operating states are modelled with the Mont Carlo method concerning multi-state generators, network configuration and loss of load probability. Research in [18] has used the Mont Carlo method and WBA for the reliability evaluation of large-scale power systems. Similar studies in [1, 7, 19] have been focused on power system WBA in the presence of WTs and ESSs. Therefore, from [11] to [15] can be concluded that the probabilistic criterion for adequacy analysis of the generation system in the presence of WTs, ESSs, etc. causes better results as compared to deterministic methods, while, from [1] to [4] can understand that WBA is better tools for generation system adequacy analysis as compared to other previous methods. WBA is a combination of deterministic and probabilistic methods, it does not have the disadvantages of the two aforementioned methods and also takes advantage of them. Therefore, this paper proposes a novel algorithm for optimal planning and operation planning of the generation part of the power system in two steps. In the first step, the number and installation capacity of TUs are determined using WBA. In the second step, economic dispatch on TUs is performed with reliability evaluation based on expected energy not served. Genetic algorithm is applied as tools for solving each step optimization problem. Therefore, the rest of the paper is organized as follows: In section 2, the concept and WBA are reviewed. In section 3, the WTs model is presented using the ARMA time series model to predict wind speed. In section 4, the reliability-based proposed flowchart is illustrated to optimal planning and operation planning of the generation system in the presence of WTs. Furthermore, in section 4, simulation studies have been implemented on a test generation system including TUs and WTs. Finally, the conceptual results are expressed in section 5.

2 WBA modelling of generation system

Reserve capacity adequacy has great importance in the system reliability and risk levels, therefore, power systems can be placed in three states such as health, margin and risk. The health condition of the system is established when reserve capacity is sufficient to satisfy the required reliability criteria. The system is in marginal condition when the reserve capacity is sufficient to supply load, but it fails to satisfy all the required reliability criteria. The system is in risk condition when the reserve capacity is not sufficient to supply load. These states are dynamic and power system situations can be changed between them. Indexes P_H, P_M and P_R are defined as health, marginal and risk states in Eq. (2.1), respectively.

$$P_R + P_M + P_H = 1 \tag{2.1}$$

Each of indexes can be calculated using statistical information, index P_R is used as loss of load probability. In most cases, indexes P_H and P_R are calculated using Capacity Outage Probability Table (COPT), after that index P_M can be calculated from (1). Outage replacement rate during lead time (T) is computed based on the repair and failure rates per year according to Eq. (2.2). If repair rate is equal to zero during lead time ($\mu = 0$) and $\lambda T \to 0$ then $P_d(T)$ can be calculated according to the Eq. (2.3).

$$P_d(T) = \frac{\lambda}{\lambda+\mu} - \frac{\lambda}{\lambda+\mu} e^{-(\lambda+\mu)T} \tag{2.2}$$

$$P_d(T) = 1 - e^{-\lambda T} = \lambda T \tag{2.3}$$

The COPT is constructed by use of FOR and ORR parameters in planning and operation planning phases of power system, respectively. Usually, system risk depends on reliability characteristic of all TUs. COPT construction is available in [3] with details.

3 WTs modelling

The WTs output power is completely depending on the wind regime and the specifications of the generator, and it can be determined in each hour with ARMA time series model using the region historical weather information during ten or twenty years [5]. For example, if, $ARMA(4,3)$ is considered as a time series according to Eq. (3.1) for a specific region then α_t is a normal white noise process with an average and variance values equal to 0 and 0.524760^2, respectively. Wind speed for WTs is calculated according to Eq. (3.1) and Eq. (3.2), which σ_t and μ_t are defined as standard deviation and the average values of wind speed measured in t hour.

$$y_t = 1.772 y_{t-1} + 0.1001 y_{t-2} - 0.3572 y_{t-3} + 0.0379 y_{t-4} + \alpha_t - 0.5030\alpha_{t-1} - 0.2924\alpha_{t-2} + 0.1317\alpha_{t-3} \tag{3.1}$$

$$SW_t = \mu_t + \sigma_t y_t \tag{3.2}$$

Simulation with $ARMA(4,3)$ for wind speed estimation ultimately lead to a probabilistic distribution, which can determine WTs output power as a function of the predicted wind speed according to the Eq. (3.3). WTs output power is determined through their operation parameters such as cut-in (V_{ci}), cut-out (V_{co}) and nominal wind speed (V_r) and output power (P_r) [5]. Parameters A, B, and C can be calculated based on cut-in and cut-out and nominal values of wind speed [7]. Here, output power of WTs is assumed as negative power absorption.

$$PP(SW_t) = \left\{ \begin{array}{ll} 0, & 0 \le SW_t \le V_{ci} \\ A + (B \times SW_t) + (C \times SW_t^2) \times P_r, & V_{ci} \le SW_t \le V_r \\ P_r, & V_r \le SW_t \le V_{co} \\ 0, & SW_t \ge V_{co} \end{array} \right\} \tag{3.3}$$

4 Proposed flowchart

In this section, the proposed flowchart is presented for optimal reliability based planning and operation planning of TUs in presence of WTs according to figure 1. It has three main sections that followed after entering the input parameters of model such as TUs minimum and maximum power capacities, outage replacement rates, force outage rates, cost coefficients and ramp rates, WTs generation capacity, network peak demand, GA parameters (p_c, p_m and iteration).

Step 1: reliability based planning of TUs in presence of WTs as an optimization problem is solved using GA. WBA is applied for the reliability evaluation. The initial population of chromosomes, which is equivalent to the initial solution for the aforementioned problem, are randomly produced for first iteration of GA algorithm according to Table 1.

Table 1: Sample chromosome is equal to the number and installation capacity of TUs in presence of WTs for generation system planning phase

$G1_1...G1_{k1}$	$G2_1...G2_{k2}$		$GL_1...GL_{kh}$		$Gn_1...Gn_{km}$

The COPT is constructed for all initial chromosomes and corresponding risk, marginal and health states probabilities are calculated for them as illustrated in the section 2. In this step, objective function is capacity installed cost minimization for TUs according to Eq. (4.1), and violations from desire system risk and health levels for each chromosome is modeled as penalty factor according to Eq. (4.2), and also sum of objective function and penalties is determined as fitness of GA according to Eq. (4.3).

$$OF^{GA}_{Planning\ Phase} = \sum_{i}^{IPPs} \sum_{j}^{Units} IC(i,j) \tag{4.1}$$

$$Penalty^{GA}_{Planning\ Phase} = \sum_{Generation\ Configuration} \left(\left| AP_r - R_r^{config} \right| + \left| AP_h - R_h^{config} \right| \right) \times 10^3 \tag{4.2}$$

$$Fitness^{GA}_{Planning\ Phase} = \min \left(OF^{GA}_{Planning\ Phase} + Penalty^{GA}_{Planning\ Phase} \right) \tag{4.3}$$

In above relations, $IC(i,j)$ is defined as the jth unit installed capacity of ith thermal power plant. Indexes AP_r and AP_h are acceptable generation system risk and health probabilities, respectively. Index R_r^{config} and R_h^{config} are risk and health probabilities for each generation system configuration which is selected as chromosome in step 1.

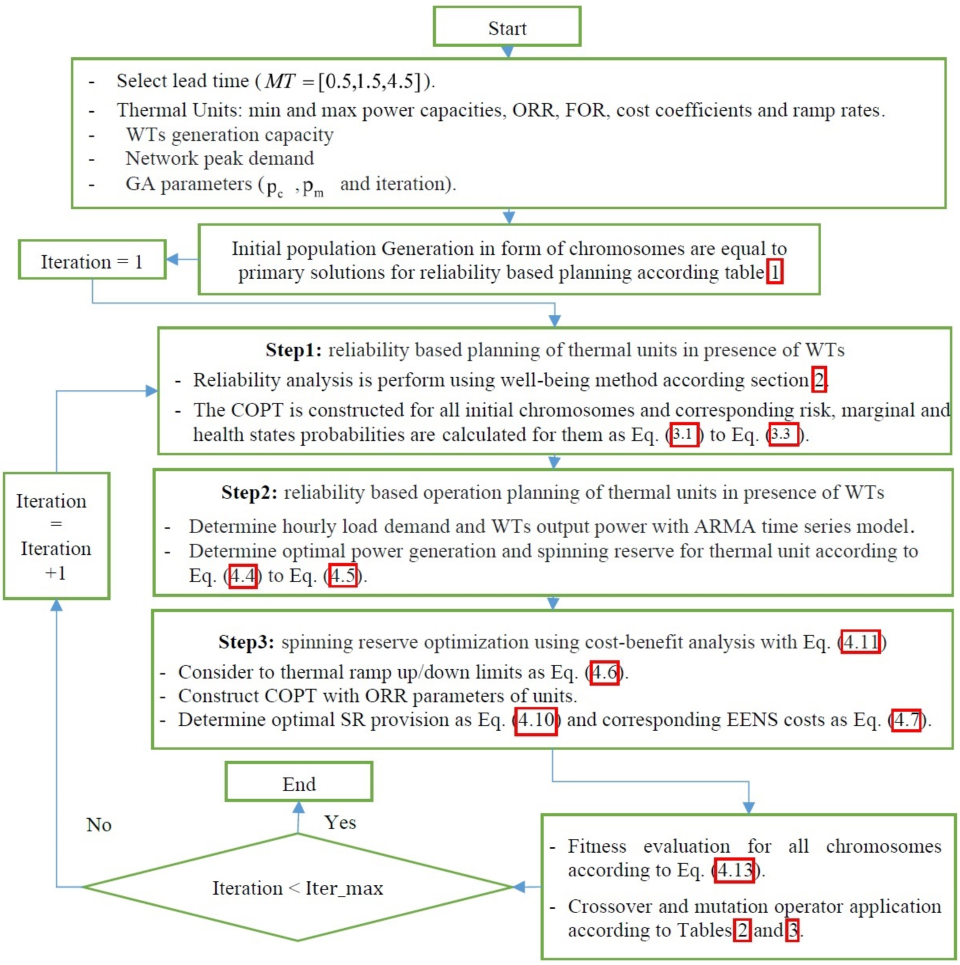


Figure 1: proposed flowchart for reliability based generation system planning and operation planning

Step 2: reliability based operation planning of TUs in presence of WTs as an optimization problem has been solved analytically. After running setp1 of flowchart, daily load economic dispatch should be done on installed capacities of TUs using bellow relations. Indexes α_{ij}, β_{ij}, and γ_{ij} are constant coefficients for TUs operation cost calculation. Indexes PG_{ij} and P^d are TU power generation and total hourly load in power system.

$$OC_{ij}(t) = \alpha_{ij} + \beta_{ij}PG_{ij}(t) + \gamma_{ij}PG_{ij}^2(t) \xrightarrow{PG_{ij}(t)=PG_{ij}(t)-1} OMWD_{ij}(t) = (\beta_{ij} - \gamma_{ij}) + 2\gamma_{ij}PG_{ij}(t) \tag{4.4}$$

$$SP(t) = \left\{ \sum_{i}^{PP} \sum_{j}^{Units} PG_{ij}(t) \right\} - P^d(t) \tag{4.5}$$

First, the seasonal, weekly and daily load demand should be determined as a percentage of the annual peak load demand. It is assumed that all TUs have been committed for full load generation. For load economic dispatch on all TUs, one MW power decreasing cost for all TUs ($OMWD_{ij}(t)$) and available generation surplus in each hour ($SP(t)$) should be calculated with respect to hourly load according to Eq. (4.4) and Eq. (4.5), respectively. Algorithm sorts TUs based on their generation decreasing costs from high to low values and produces a priority list. TU with higher order in priority list is selected and then one MW is decreased from its power generation. If, load demand and power generation balance is satisfied then algorithm will be interrupted, otherwise bellow work should be performed:

- At this condition, the variables $OMWD_{ij}(t)$ and $SP(t)$ should be computed according relation (4.4) and Eq. (4.5), again.
- Next one MW is decreased from first order TUs in priority list.
- If, power generation of first order TUs in priority list gets to its minimum generation limit then likewise process will be continued with second order TU.

Mentioned process is repeated until power generation and load balance is satisfied ($SP = 0$). This analytical algorithm is repeated for all operational time intervals.

Step3: although, calculated spinning reserves on committed TUs in step2 are suboptimal ($SR_{ij}^{Sub-opt}$) because don't consider to units ramp up/down rate during occurrence single contingencies events. Therefore, spinning reserve should be optimized in each operation time interval. Here, a new analytical method is proposed for spinning reserve optimization. To achieve this goal, first, available spinning reserve should be computed considering the ramp rates of TUs (SR_{ij}^{Ava}) according to Eq. (4.6). If, expected cost of energy not served is calculated as relation (4.7), then probability of single contingency event (Pr_{ik}^{Outage}) for various system states is defined as Eq. (4.8). Load shedding value corresponding to each single contingency event (PL_{ik}^{shed}) is determined by Eq. (4.9).

$$SR_{ij}^{Ava}(t) = \min(RR_{ij}, SR_{ij}^{Sub-opt}) \tag{4.6}$$

$$EENS(t) = \sum_{i} \sum_{k} \left\{ Pr_{ik}^{Outage}(t) \times PL_{ik}^{shed}(t) \right\} \to EENS_{Cost}(t) = EENS(t) \times Voll_{ave} \tag{4.7}$$

$$Pr_{ik}^{Outage}(t) = ORR_{ik}^{Outage}(t). \prod_{h=ij,\ ij \neq ik} (1 - ORR_{ij}^{Outage}(t)) \tag{4.8}$$

$$PL_{ik}^{shed}(t) = \begin{cases} 0, & \to Tot^{SR}(t) \geq PG_{ik}^{Ava} \\ PG_{ik}^{Available} - \sum_i^{PP} \sum_j^{Units} SR_{ij}^{Opt}(t), & \to Tot^{SR}(t) \prec PG_{ik}^{Ava} \end{cases} \tag{4.9}$$

In above relation, Index ORR_{ik}^{Outage} is defined as outage replacement rate after kth TU outage of power plant ith, and Index $Voll_{ave}$ is average value of lost load for customers. Since, power plant owners declare the spinning reserve provision cost in accordance with a percentage of their energy production marginal cost (MP_{ij}) according to Eq. (4.10), therefore, cost-benefit analysis can be possible between spinning reserve provision cost increment and expected cost of energy not served decrement for optimal reserve determination (SR_{ij}^{Opt}) according to Eq. (4.11).

$$SR_{ij}^{Price}(t) = \%k \times MP_{ij}(t) \to Tot_{Cost}^{SR}(t) = \sum_{i}^{PowerPlant} \sum_{j}^{Units} SR_{ij}^{Opt}(t) \times SR_{ij}^{Price}(t) \tag{4.10}$$

$$Cost\&BenefitAnalysis \to \begin{cases} Tot_{Cost}^{SR}(t) \leq Tot_{Budget}^{sr}(t) \\ \Delta Tot^{SR}(t) \leq \Delta EENS_{Cost}(t) \end{cases} \tag{4.11}$$

After ending step 3, for all chromosomes in iteration 1 of proposed flowchart, fitness should be updated with generation system operation cost ($\sum_i^{PP}\sum_j^{Units} OC_{ij}(t)$) and reliability cost ($EENS_{Cost}(t) + Tot_{Cost}^{SR}(t)$) on all time periods according to Eq. (4.12) and Eq. (4.13).

$$OF_{OP\ Phase}^{GA} = \sum_{t=1}^{n}\left(EENS_{Cost}(t) + Tot_{Cost}^{SR}(t) + \sum_{i}^{PP}\sum_{j}^{Units} OC_{ij}(t)\right) \tag{4.12}$$

$$Fitness^{GA} = \min\left(OF_{P\ Phase}^{GA} + OF_{OP\ Phase}^{GA} + Penalty_{P\ Phase}^{GA}\right) \tag{4.13}$$

After sorting the chromosomes based on their fitness, Crossover operator according Table 2 is imposed to all pair chromosomes with probability P_c to construct new chromosome as child, randomly. Then, mutation operator according Table 3 is imposed to some chromosomes with probability P_m to construct new chromosome as mutated child. In proposed algorithm, same process on new chromosomes population at next iteration is done for removing chromosomes penalties. This work continuous until convergence condition is satisfied.

Table 2: crossover operator application for pair chromosomes

$G1_1...G1_{k1}$	$G2_1...G2_{k2}$		$GL_1...GL_{kh}$			$Gn_1...Gn_{km}$
1,1,1,…1	1,1,0,…0		1,0,0,….0			1,0,0,….0
$G1_1...G1_{k1}$	$G2_1...G2_{k2}$		$GL_1...GL_{kh}$			$Gn_1...Gn_{km}$
1,1,1,…0	1,0,0,…0		1,1,1,….0			1,1,1,….0
⇩	⇩					
$G1_1...G1_{k1}$	$G2_1...G2_{k2}$		$GL_1...GL_{kh}$			$Gn_1...Gn_{km}$
1,1,1,…0	1,0,0,…0		1,0,0,….0			1,0,0,….0
$G1_1...G1_{k1}$	$G2_1...G2_{k2}$		$GL_1...GL_{kh}$			$Gn_1...Gn_{km}$
1,1,1,…1	1,1,0,…0		1,1,1,….0			1,1,1,….0

Table 3: mutation operator application on chromosomes

$G1_1...G1_{k1}$	$G2_1...G2_{k2}$		$GL_1...GL_{kh}$			$Gn_1...Gn_{km}$
1,1,1,…0	1,0,0,…0		1,0,0,….0			1,0,0,….0
			⇩			
$G1_1...G1_{k1}$	$G2_1...G2_{k2}$		$GL_1...GL_{kh}$			$Gn_1...Gn_{km}$
1,1,1,…0	1,0,0,…0		0,0,1,….0			1,1,1,….0

To validate the efficiency and effectiveness of the proposed model, Simulation studies have been applied on the standard generation system with 32 TUs and 25 WTs with 2MW capacity according to Fig. 2. The annual peak load demand is equal to 2850 MW.

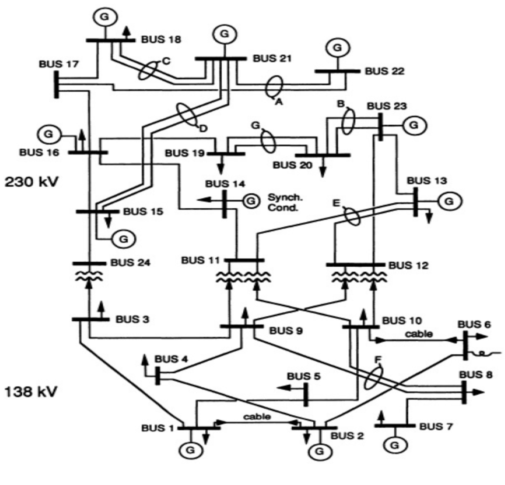


Figure 2: The 24-bus IEEE standard test power system

As can be seen from the above figure, there are two voltage levels in the power network including 230 KV and 138 KV. The transmission network has 24 buses 5 transformers and 34 transmission lines. There are ten thermal power plants with 32 generating units which are installed at bus1, bus2, bus7, bus13, bus14, bus15, bus16, bus18, bus21, bus22 and bus23. Technical information about thermal power plants has been displayed in Table 4 and Table 5 [9]. The wind farm is installed on bus10, and the output power of WTs is estimated with the ARMA time series model. The average and standard deviation of wind speed in the region are 22.46m/s and 5.7m/s, respectively and also cut-in and cut-out and normal wind speeds are 40m/s, 5m/s and 20m/s, respectively.

Table 4: Technical information including TU numbers, capacities, ramp rates, installed cost and failure rates

TUs						
GenCos	**Number of units**	**Pmax**	**Pmin**	**RR**	**IC**	λ
Gen1	4	50	0	10	50000	4.42
Gen2	2	400	200	0	650000	7.96
Gen3	1	350	150	9	600000	7.62
Gen4	3	197	80	6	328000	9.22
Gen5	4	155	60	5	285000	9.13
Gen6	3	100	40	3	228000	7.30
Gen7	4	76	25	2	105000	4.47
Gen8	5	12	0	1	35000	2.98
Gen9	4	20	0	4	42000	19.47
Gen10	2	50	0	10	100000	4.47

Table 5: Technical information including TU's cost coefficients

TUs			
GenCos	α	β	γ
Gen1	0	0.5	0
Gen2	216.576	5.345	0.00028
Gen3	301.233	20.023	0.00300
Gen4	206.703	9.2706	0.00667
Gen5	206.703	9.2706	0.00667
Gen6	216.703	9.2706	0.00667
Gen7	220.703	9.3706	0.00667
Gen8	226.703	9.3706	0.00669
Gen9	236.703	9.4706	0.00668
Gen10	256.703	9.3706	0.00677

Numerical studies have been implemented on a 24-bus IEEE test power system with the goal of optimal generation system planning and operation planning using reliability analysis according to the proposed flowchart. GA parameters such as Pc, Pm, and Iteration are 0.7, 0.3 and 50. The initial population is considered 1000. Proposed model codes are written in MATLAB software that is installed on an ASUS laptop with a 7-core and 2.4GHz processor and 8GB RAM.

4.1 First case study: optimal reliability based generation system planning and sensitivity analysis

In this section, optimal generation system planning is solved by GA with and without reliability constraints. Acceptable system risk and health levels probabilities are 0.001 and 0.95, respectively. Sensitivity analysis is applied with changes in the system lead time as 0.5 hours, 1.5 hours and 4.5 hours. Simulation results are shown in Fig 3a to 3d.

According to Fig (3a), if, generation system planning does not pay attention to the acceptable risk and health probabilities constraints then 16 TUs including 3 units of Gen7, 3 units of Gen6, 4 units of Gen5, 3 units of Gen4, 1 unit of Gen3 and 2 units of Gen2 along with 50 MW of WTs generation capacity should be installed to supply annual peak load demand. The operating reserve is 39MW and generation system risk, marginal and health states probabilities are determined as 0.0070184, 0.99298156 and 0, respectively. But, according to Fig (3b, 3c and 3d), if generation system planning is implemented about the acceptable risk and health probabilities constraints, then selected numbers

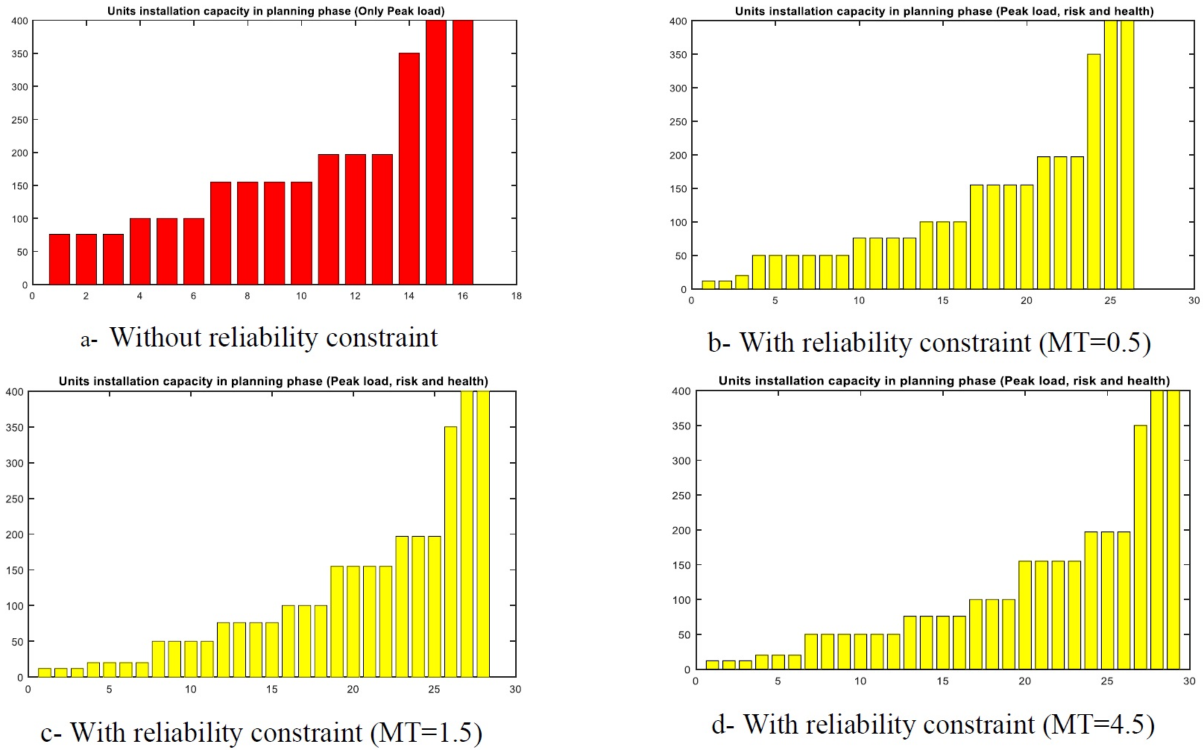


Figure 3: Generation system optimal planning and sensitivity results

and capacities of TUs beside WTs capacity will be increased corresponding to system lead time increment from 0.5 to 1.5h and 0.5h to 4.5h. Simulation results are shown in Table 6. it can be seen generation system risk and health probabilities are lower and greater than predetermined acceptable levels, respectively. Simulation results show that the number of TUs is 26, 28 and 29 for lead times 0.5h, 1.5h, and 4.5h, respectively.

Table 6: Simulation results for sensitivity analysis based on generation system lead time

System lead time	**Variable values**		
	$A_r = 0.001$		$A_H = 0.95$
	$\tau = 0.5$	$\tau = 1.5$	$\tau = 4.5$
n_{TH}^{Opt}	26	28	29
IC_{TH}^{Opt}	5640000	5701000	5759000
SR_{TH}^{Opt}	459	431	511
Pr_R^{GS}	7.6177×10^{-6}	81.662×10^{-6}	383.18×10^{-6}
Pr_H^{GS}	0.9927	0.97526	0.95492
Pr_M^{GS}	0.00726	0.024655	0.04468

It can be concluded that the total capacity investment costs of TUs will increase with system risk probability increment and system health probability decrement. With increasing system lead time, the probability of the generation system being placed in a margin risk situation is increased from 0.00726 to 0.04468 and the probability of the generation system being placed in a health situation is decreased from 0.9927 to 0.95492.

4.2 Second case study: optimal reliability based generation system operation planning

In this case study, generation system operation planning has been considered with generation system reliability consideration. The optimal amount of power generation and spinning reserve for TUs in the presence of WTs resources are determined. The hourly output power of WTs resources is represented by the ARMA time series model following Fig 4.

Hourly load demand and corresponding LDC curve is shown in Fig 5a to 5b. Lead time is equal to 4.5h.

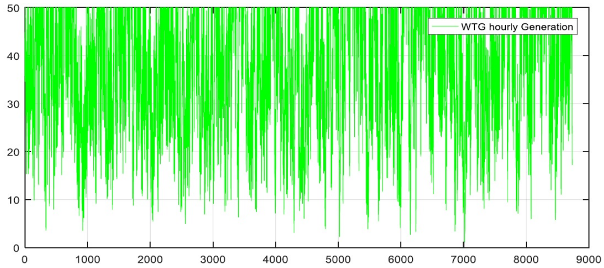
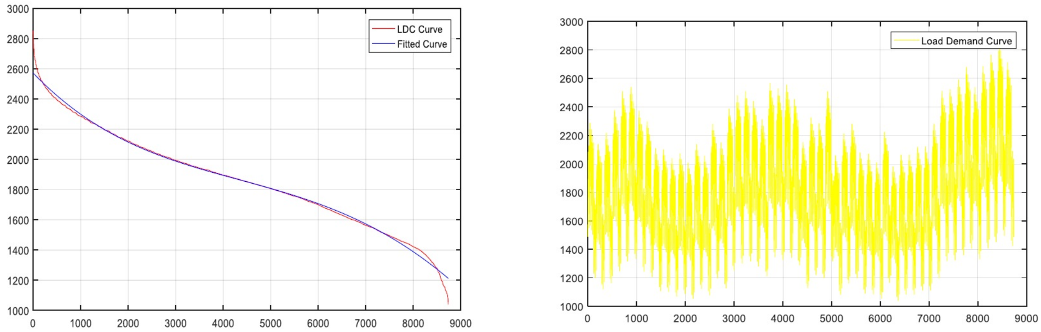


Figure 4: Hourly output power of WTs resources with the ARMA time series model



a

b

Figure 5: load duration curve (a) and load demand (b) for a year.

The simulation results for load economic dispatch on TUs are displayed in Fig 6. In addition, the optimal power generations by the largest (cheapest) and smallest (most expensive) units have been depicted in form of two dimensional diagram.

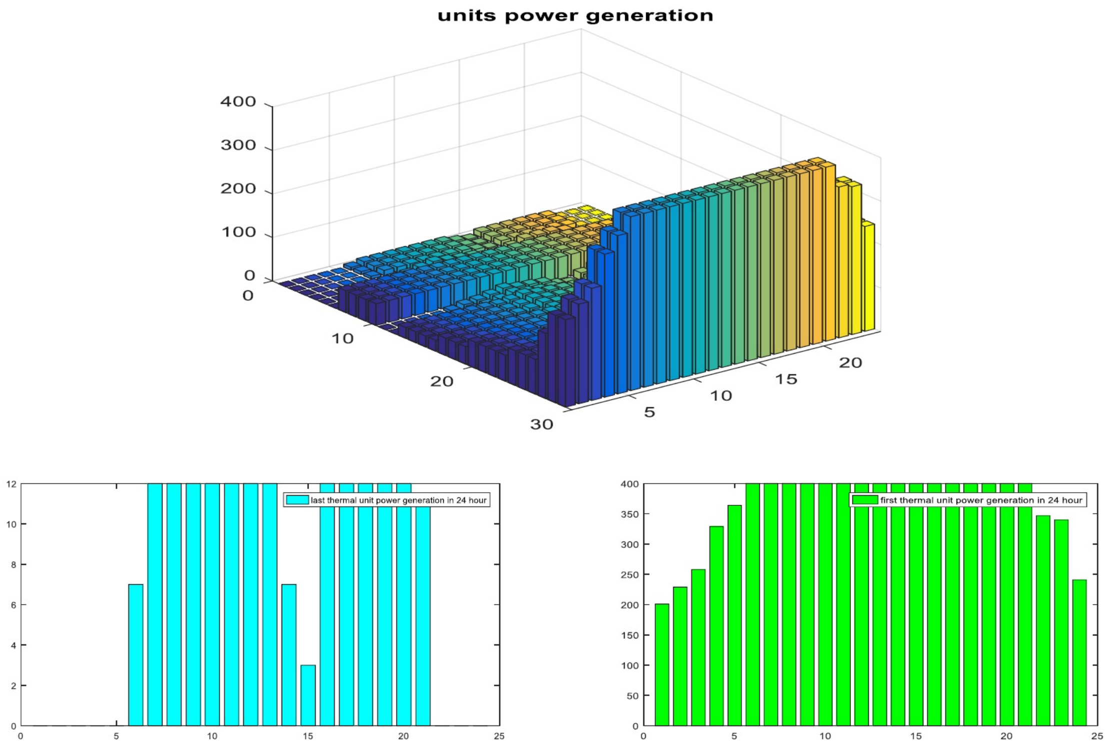


Figure 6: The simulation results for load economic dispatch on TUs

Simulation results reveal that the cheapest units are committed with full power generation capacity for most of the 24 time periods except a few primary and last periods, while expensive units are committed for power generation only during the morning and evening peak hours and experience reverse conditions. It should be noted that here the average value of lost load for customers is 10,000 $\$/MWh$. The spinning reserve provision cost for TU is considered 5% of the power generation marginal cost. Fig 7 shows the simulation results for all TU's unloaded synchronized capacity, available capacity and optimal price and amount of spinning reserve during the first day of the year.

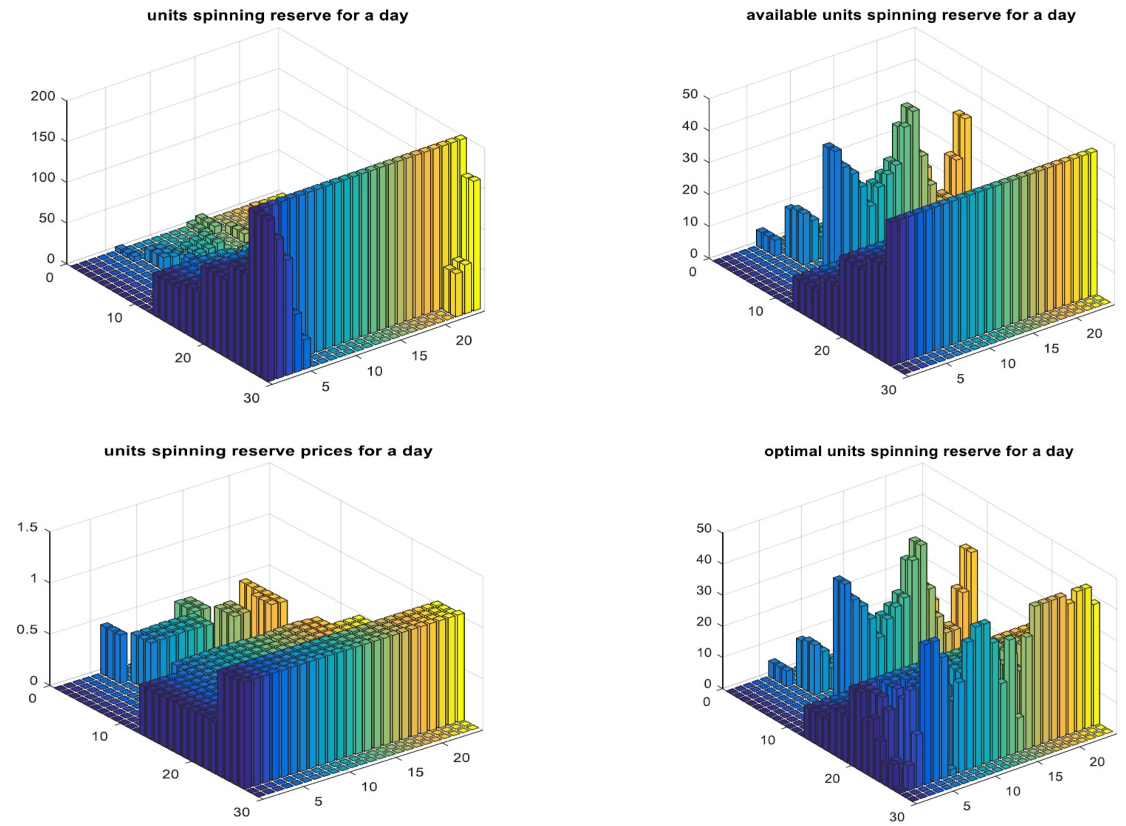


Figure 7: Simulation results for all TU's unloaded synchronized capacity, available capacity and optimal amount of spinning reserve during first day of year

As can be concluded from the simulation results, all TU's synchronized unloaded capacity during the periods of operation planning is impressive, but their maximum available capacities are limited to the amounts of unit's ramp up rate. Optimal amount of spinning reserve on all units are calculated using cost-benefit analysis between EENS and SR provision costs according to Fig 8.

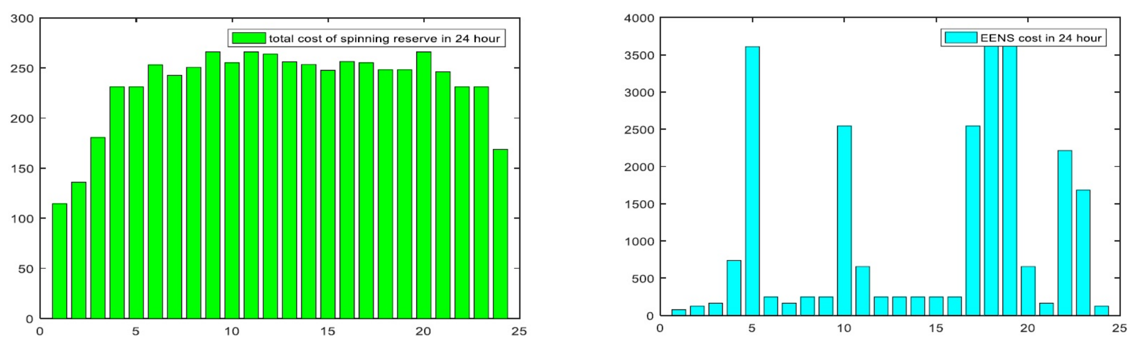


Figure 8: Simulation results for optimal amount of EENS and SR provision costs

Simulation results indicate that paying the optimal amount of money for spinning reserve provision in the range of 110 dollars to 270 dollars can prevent economic damages to customers in the range of 500 dollars to 3800 dollars, approximately. Therefore, it can be perceived that providing the optimal amount of spinning reserve on TUs will be an essential task in the system operation planning phase from the operator's point of view.

5 Conclusion

In this paper, a new algorithm is proposed for reliability-based planning and operation planning of TUs in the presence of WT resources. GA method is used for the aforementioned optimization solution. The main goal in the reliability-based planning phase is to meet the annual peak load while the desirable level of system risk and health probabilities are satisfied. WBA is applied for generation system reliability evaluation in the planning phase. Daily Load economic dispatch and spinning reserve optimization for TUs in the presence of WTs is determined at the reliability-based operation planning phase. Expected energy not served cost has been introduced for spinning reserve provision in the operation planning phase through cost-benefit analysis. During the operation planning phase, the output power of WTs is estimated using the ARMA time series model. To validate the proposed algorithm, Simulation studies have been applied to the standard generation system with 32 TUs and 25 WTs with 2MW capacity. From simulation results can be concluded that the total capacity investment costs of TUs in the generation system planning phase will increase with system risk probability increment and system health probability decrement. With increasing system lead time, the probability of the generation system being placed in a marginal risk situation is increased and the probability of the generation system being placed in a healthy situation is decreased. Simulation results in the generation system operation planning phase reveal that the cheapest units are committed with full power generation capacity for all times except a few primary and last periods, while expensive units are committed for power generation only during peak periods. In addition, paying the optimal amount of money for spinning reserve provision can cause to significant decrease in economic damages to customers.

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