Engineering Applications of Artificial Intelligence 37 (2015) 236–249

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Multi-objective unit commitment with introduction of a methodology for probabilistic assessment of generating capacities availability

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ARTICLE INFO

Article history:
Received 19 April 2014
Received in revised form
6 July 2014
Accepted 18 September 2014
Available online 11 October 2014

Keywords:
Unit commitment
Generation dispatch
Power system
Unavailability
Genetic algorithm
Multi-objective optimization

ABSTRACT

The goal of the short-term unit commitment is the minimization of the total operation cost while satisfying all unit and system constraints. One of the main issues while solving the unit commitment optimization problem is the planning of the capacity reserves of the power system. In order to address this issue, a dynamic method for probabilistic assessment of generation unavailability is proposed within this paper. The main highlight feature of this method is that it has the capacity to account for the unavailability implications of the generating unit states, being committed or decommitted as well as their start-up characteristics. This allows more comprehensive hour-to-hour scheduling analyses from the aspect of probabilistic unavailability assessment. The generating capacities unavailability is designated as the relevant unavailability measure regarding the power supply to loads. The unit commitment problem is developed as a multi-objective optimization problem. Two objective functions are considered: the total operating cost of the generating capacities as one and generating capacities unavailability as the other objective function. An improved hybrid genetic algorithm is applied for solving the problem. A test power system is used as a case study. The obtained results indicate the need and benefits of more detailed modelling of the power generation availability.

1. Introduction

The general idea behind the short-term unit commitment (UC) is meeting the forecasted load on a short-term basis (one day or up to one week) by accordingly scheduling the on or off line status of the generating capacities (Cheng et al., 2002). The objective of the short-term UC is the minimization of the total operation cost while satisfying all unit and system constraints. The UC problem is highly constrained, non-linear, mixed integer optimization problem. The exact solution of the problem can be obtained by complete enumeration, a process which is not computationally feasible for realistic power systems (Orero and Irving, 1997; Wood and Wollenberg, 1996).

Modern meta-heuristic algorithm based techniques have been extensively employed for solving generation scheduling problems. One of the first applications of genetic algorithm (GA) on the generation (economic) dispatch optimization problem is shown in Ref. Walters and Sheble (1993). Approximately in the same period the simulated annealing (SA) algorithm was also applied for the optimal generation dispatching (Wong and Fung, 1993). Since then various modern techniques have been used for the single objective and multi-objective generation dispatch problem. In Ref. Elsayed et al. (2014) a new GA has been proposed for solving engineering problems including optimal generation dispatching. A modified particle swarm optimization has been used on the static generation dispatch problem considering valve point-effects and prohibited operating zones (Neyestani et al., 2010). Ref. Lu et al. (2011) introduces three novel chaotic differential evolution techniques for solving the dynamic generation dispatch problem.

UC problem is another part of the generation scheduling that was solved with modern meta-heuristic algorithms. Since beginning of the 1990s, when the GAs were first employed in power system optimization, they have become very popular tool for solving the UC problem. In Ref. Dasgupta and McGregor (1994) the application of a binary coded GA has been discussed for solving the UC problem. Similar study was presented in Ref. Kazarlis et al. (1996) where Kazarlis et al. applied a binary coded GA on a 10-unit test system. The results in this study are compared with classical techniques such as dynamic programming (DP) and Lagrange relaxation (LR). Later on, the application of a real coded GA for the UC problem was discussed (Damousis et al., 2004). It was shown that real coded GA can produce better results than the LR method that was used as a benchmark in the paper, also the execution time of the algorithm was reduced compared to the binary coded GA. Other modern meta-heuristic techniques have

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http://dx.doi.org/10.1016/j.engappai.2014.09.014
0952-1976/

been extensively used for the UC problem as well, such as: evolutionary programming (Juste et al., 1999), neural networks (Ouyang and Shahidehpour, 1992), simulated annealing (Mantawy et al., 1998), particle swarm optimization (Ting et al., 2006), ant colony (Simon et al., 2006) and artificial bee colony algorithm (Chandrasekaran et al., 2012).

A careful planning of the reserves is required in the short-term UC schedule in order to ensure an adequate reliability level. Even though most of the above-mentioned techniques offer an acceptable solution for the UC problem, they are using old and most commonly used methods for reserve planning, i.e. low margin as a percentage from the real system load at each time interval and the reserve equal to the power output of one or more of the largest units. These methods can lead to overscheduling which means more reliable and uneconomic unit commitment as well as underscheduling which means more economic and less reliable unit commitment. However, some studies, where probabilistic reserve evaluation is used, have been performed. Dillon et al. presented a probabilistic method for proper representation of the reserves associated with different unavailability levels (Dillon et al., 1978). The developed model is integrated within the short-term UC as constraint that has to be satisfied. This model ensures that a given reliability level is achieved. Similar approach is used in Ref. Shi et al. (2004) where a stochastic mechanism is developed for the short-term UC with probabilistic determination for spinning reserve constraint. In Ref. Lee and Chen (2007) a method for solving the short-term UC problem with probabilistic reserves is discussed. In Ref. Simopoulos et al. (2006) evaluation of the required spinning reserve capacity is performed by applying reliability constraints based on loss of load probability (LOLP) and expected energy not supplied (EENS) indices. Similar approach is presented in Ref. Jalilzadeh et al. (2009) where a dynamic penalty constraint is applied for the EENS constraint. A two-level, two-objective optimization scheme based on evolutionary algorithms for solving UC problem by considering stochastic power demand variations is proposed in Ref. Georgopoulou and Giannakoglou (2009). The total operating cost is used as one objective while the risk of not fulfilling possible demand variations is used as the second objective to be minimized. In other words the paper investigates the trade-off between total cost and the risk due to load uncertainties. In Ref. Lei et al. (2008) the loss of load expectation (LOLE) is included as a constraint in the long-term UC for calculating the cost of supplying the reserve. In Ref. Bouffard and Galiana (2004) an algorithm is developed that includes the scheduling of spinning reserve according to a hybrid deterministic/probabilistic reliability criterion. This hybrid criterion behaves consistently with purely probabilistic criteria such as LOLP. In most of these methods an optimal reserve planning is achieved when a probabilistically determined generating reserve is used as controlled criteria/constraint, instead of an independent objective function. Additionally, most of these techniques do not account for the implications for unavailability of the commitment of a specific unit at given time interval and the time needed for these units (rapid-starting, slow-starting) to be online and start generating. These are the main motivations for the work done in this study.

The increased reliability of power supply corresponds to increased costs (Billinton and Allan, 1988). The same rationale is valid for the short-term unit commitment. This research is focused on the interdependence between the total cost of power production, the capacity outage unavailability and generation reserves in the short-term UC. The main objective of this study is to develop a dynamic method for power system probabilistic unavailability evaluation. The generating capacities unavailability is the relevant unavailability measure. As such, the LOLP is used as an unavailability index herein. This approach has the capacity to account for the time inertia related to different generating units to be online and start generating. The second objective of the paper is performing trade-off analysis between the total production costs and the capacity outage unavailability. Therefore, the UC is presented as a multi-objective optimization problem. For comparative purposes a deterministic model is introduced as well. This deterministic model is defined as a function of the spinning reserve.

For solving the short-term UC optimization problem an improved hybrid GA is constructed. The algorithm uses classical method, i.e. priority list in order to create the initial population. An improvement of the classical hybrid GA (Orero and Irving, 1997) is proposed by employing hybrid solutions additionally within the initial population. The algorithm employs repairing mechanisms and penalization technique to deal with the constraint violations. The UC problem is solved in three separate formulations. Firstly, the problem is solved as a single objective, once considering the total production cost objective function and secondly, considering the generation unavailability function. At the end, the problem is solved as a bi-objective, considering both of the objective functions. Two scenarios are analysed: considering and not considering the spinning reserve constraint. The obtained results show that compromise between cost and unavailability is achieved. Additionally, improvements on the used test power system are proposed and the system as such is solved using the same model. For verification purposes, the used algorithm has been applied on a 10, 20, 40, 60, 80 and 100 unit systems and the obtained results were compared with others available in the literature.

2. Power system reliability

The primary objectives of the modern power systems are to provide a reliable and economic supply of electric energy to their customers. The main issue in the planning and also in the operating phases has always been the adequate reserves of generating capacity. Consequently, the level of redundancy and the associated cost are designated as the prime question. By definition, the reserve capacities that are spinning, synchronized and ready to take up load are known as spinning reserve. Some power system operators include only the spinning reserve in the assessment of system adequacy, while others include also the rapid start units such as gas turbines and hydropower plants or assistance from the interconnected systems. These additional factors added to the spinning reserve are all together known as operating reserve (Billinton and Allan, 1996). The operating capacity domain, i.e. the short-term unit commitment is of interest in this research paper.

In general, each power system operation is associated with prediction of the expected load, i.e. short-term load forecasting, and consequently providing for and scheduling of sufficient generation capacity. The time needed for a specific generating unit to produce an output ranges from few minutes in the case of gas turbines and hydropower plants to several hours in the case of thermal generating power plants. This is especially important for the intermediate load units which are mostly coal-fired units that have considerable starting inertia (several hours). If an unexpected change occurs in the power system and additional generation is required immediately, the intermediate load units cannot be counted for at this point of time if they are not committed and spinning. Therefore, within the probabilistic unit commitment evaluation these units should be considered as unavailable in the time interval when they are decommitted.

Various design, planning and operating criteria and techniques have been developed over many decades in an attempt to resolve and satisfy the dilemma between the economic and reliability constraints (Billinton and Allan, 1996). Most of these criteria and techniques are inherently deterministic. However the power systems behave stochastically. The main weakness of these methods is that they cannot account for the stochastic nature of the system (Čepin, 2011).

3. Multi-objective unit commitment

The term unit commitment is associated with the strategic choice to be performed in order to identify the generating capacities of a given power system, designated to be used in order to meet the forecasted load demand over a future short-term (Amjady and Shirzadi, 2009; Yan-Fu et al., 2013). In this paper, the UC optimization problem is developed as a multi-objective optimization problem.

Recently several methods for multi-objective unit commitment have been shown in the scientific literature. In Ref. Norouzi et al. (2014) a method for the combined economic–environmental short-term unit commitment for hydro and thermal generation units is presented. Two objectives are considered, the total operating cost and gaseous emission caused by the thermal units. The problem is transformed into mixed integer linear programming. The Pareto optimal solutions are derived by employing lexicographic optimization and hybrid augmented-weighted ε-constraint technique. The combined economic–environmental short-term unit commitment is also solved in Ref. Yan-Fu et al. (2013). The NSGA-II algorithm is used for the multi-objective optimization. A novel two-phase approach for the multi-objective unit commitment problem is presented in Ref. Li et al. (2013). In the first phase, hourly-optimal scheduling is done to simultaneously minimize total cost, gaseous emission, and transmission loss, while satisfying constraints such as power balance, spinning reserve and power generation limits. In the second phase, the minimum up/down time and ramp up/down rate constraints are solved.

In this study two objective functions are considered: the total operating cost of the generating capacities as one and generating capacities unavailability as the other objective function. In other words, the objective of the unit commitment problem is the simultaneous minimization of the total operating costs and the generating capacities unavailability over the scheduling period while meeting the load demands and satisfying all units and system constraints. One-day time period is chosen and divided in 24 intervals each lasting one hour.

3.1. Total operating cost objective function

The total operating costs over the scheduling period are comprised of the fuel costs, start-up costs and shut-down costs and can be expressed as follows:

$$F_T = \sum_{t=1}^{T}\sum_{i=1}^{N}[S_{i,t}F_{C_i}(P_{G_{i,t}})+CU_iS_{i,t}(1-S_{i,t-1})+CD_iS_{i,t}(1-S_{i,t+1})] \tag{1}$$

where F_{C_i} is the fuel cost, $S_{i,t}$ is the on/off status of the ith unit at the tth hour, with $S_{i,t}=1$ when the unit is on and $S_{i,t}=0$ when the unit is off, $P_{G_{i,t}}$ is the power output of the ith thermal unit at the tth hour, CU_i is the start-up cost of the ith unit, CD_i is the shut-down cost of the ith unit, T is the total scheduling period and N is the total number of units.

The most frequently used fuel cost function is written in quadratic form (Dillon et al., 1978; Kazarlis et al., 1996) as follows:

$$F_{C_i}\left(P_{G_{i,t}}\right) = a_i+b_iP_{G_{i,t}}+c_iP_{G_{i,t}}^2+\left|d_i \sin\left\{e_i\left(P_{G_{i,t}}^{min}-P_{G_{i,t}}\right)\right\}\right| \tag{2}$$

where a_i, b_i and c_i are the cost coefficients and d_i and e_i are valve point coefficients.

The start-up cost of a thermal generating unit can be calculated as an exponential function of the off time (Dieu and Ongsakul, 2011) as follows:

$$CU_i = \alpha_i+\beta_i\left[1-\exp\left(-\frac{T_{i,t-1}^{off}}{\gamma_i}\right)\right] \tag{3}$$

where α_i, β_i and γ_i are the start-up coefficients of the ith thermal unit and $T_{i,t}^{off}$ is duration for which the ith thermal unit has been continuously off until hour t. A simplified approach for calculation of the start-up cost is used in this study as follows:

$$CU_i = \begin{cases} H_{C_i};\ T_i^{down} < T_{i,t}^{off} \le T_i^{down}+T_i^{cold} \\ C_{C_i};\ T_{i,t}^{off} > T_i^{down}+T_i^{cold} \end{cases} \tag{4}$$

where H_{C_i} and C_{C_i} are the hot start-up cost of and cold start-up cost of the ith thermal unit, T_i^{down} is the minimum down time of the ith thermal unit and T_i^{cold} is the cold start hour of the ith thermal unit.

3.1.1. Constraints

3.1.1.1. Power balance constraints. The power balance constraints require that the sum of all generated power outputs from all online generating units is equal to the load demands plus the power losses in the system:

$$\sum_{i=1}^{N} P_{G_{i,t}}S_{i,t} = P_{L_t}+P_{loss_t} \tag{5}$$

where P_{L_t} and P_{loss_t} are the load demand and the power losses in the system at tth hour respectively.

3.1.1.2. Generating capacity constraints. The generator capacity constraints are expressed as follows:

$$\begin{cases} P_{G_i}^{min} \le P_{G_{i,t}} \le P_{G_i}^{max} & \text{when} \quad S_{i,t}=1 \\ P_{G_{i,t}}=0 & \text{when} \quad S_{i,t}=0 \end{cases} \tag{6}$$

where $P_{G_i}^{min}$ and $P_{G_i}^{max}$ are the minimum and maximum power outputs for the ith unit respectively.

3.1.1.3. Operating ramp rate constraints. The operating ramp rate constraints are defining the allowed change in power during one time interval (hour):

$$P_{G_{i,t}}-P_{G_{i,t-1}} \le UR_i \quad \text{if } S_{i,t}=1 \text{ and } S_{i,t-1}=1 \tag{7}$$

$$P_{G_{i,t-1}}-P_{G_{i,t}} \le DR_i \quad \text{if } S_{i,t}=1 \text{ and } S_{i,t-1}=1 \tag{8}$$

where UR_i and DR_i are the operating ramp-up and rump-down rate per hour of the ith thermal unit respectively.

3.1.1.4. Start-up and shut-down ramp rate constraints. The start-up and shut-down ramp rate constraints are limiting the unit power as the unit starts up and shuts down respectively:

$$P_{G_{i,t}}-P_{G_{i,t-1}} \le SUR_i, \quad \text{if } S_{i,t}=1 \text{ and } S_{i,t-1}=0 \tag{9}$$

$$P_{G_{i,t-1}}-P_{G_{i,t}} \le SDR_i \quad \text{if } S_{i,t}=0 \text{ and } S_{i,t-1}=1 \tag{10}$$

where SUR_i and SDR_i are the start-up ramp constraint and shut-down ramp constraint of the ith thermal unit respectively.

3.1.1.5. Minimum up and down time constraints. Once a unit is committed, there is a minimum time before the unit can be decommitted and vice versa:

$$\begin{cases} T_i^{up} \le T_{i,t}^{on} \\ T_i^{down} \le T_{i,t}^{off} \end{cases} \tag{11}$$

where T_i^{up} is the minimum up time of the ith thermal unit and $T_{i,t}^{on}$ is the duration for which the ith thermal unit has been continuously on until tth hour.

3.1.1.6. System reserve requirements. Hourly spinning reserve requirements, R_t, must be met:

$$\sum_{i=1}^{N} P_{G_{i,\ max}} S_{i,t} \geq P_{L_t} + P_{loss_t} + R_t \tag{12}$$

3.1.1.7. Must run units. The term must-run unit is related to those generating capacities which due to economic and system reliability consideration are continuously committed during all of the scheduling period. In practice, these units are usually the base load units, i.e. the largest thermal units in the power system.

3.1.1.8. Prohibited operating zones constraints. A prohibited operating zone of a unit is a range of power outputs where the unit is not allowed to operate. A unit may have one or more prohibited operating zones. Mathematically the prohibited operating zones constraint is formulated (Özyön and Aydin, 2013) as follows:

$$P_{G_i} \in \begin{cases} P_{G_i}^{min} \leq P_{G_i} \leq P_{G_{i,1}}^{l} \\ P_{G_{i,j-1}}^{u} \leq P_{G_i} \leq P_{G_{i,j}}^{l} \quad \text{where} \quad j = 2, 3, \ldots, n_i \\ P_{G_{i,n_i}}^{u} \leq P_{G_i} \leq P_{G_i}^{\max} \end{cases} \tag{13}$$

where $P_{G_{i,j}}^{u}$ and $P_{G_{i,j}}^{l}$ are the lower and upper limits of the prohibited operating zones of the ith generation unit, respectively and n_i is the number of the prohibited operating zone of the ith generation unit.

3.2. Generating capacities unavailability objective function

The calculation of the unavailability related to solving the unit commitment problem is associated with the identification of the unit or units to be committed in any given time interval over the scheduling time period (Billinton and Allan, 1996). One of the oldest and traditionally applied methods for reserve planning is the method that sets the reserve equal to the power output of one or more of the largest units. Another similar method designates a low margin as a percentage of the load demand at each time interval. These traditional methods do not give any accurate information about how much the scheduled reserves are valuable for the power system reliability. That is why probabilistic evaluations are needed in order for the approach to become more consistent and closer to the real scenario. The rationale behind is that such a method would implicate more objective decision making (Billinton and Allan, 1996).

The two-state model is used for representation of the generating unit unavailability. However, the generating unit unavailability model is not limited to these two states. Instead, multiple derated states with discrete probabilities may also be considered. Based on the two-state model the unavailability of generating unit, U_{un_i}, at time interval, LT, considering that the unit was available at $t=0$ is calculated (Billinton and Allan, 1996; Guangbin and Billinton, 1994) as follows:

$$U_{un_i} = \left(1 - e^{-(\lambda_i + \mu_i)LT}\right)\frac{\lambda_i}{\lambda_i + \mu_i} \tag{14}$$

where λ_i and μ_i are failure and the repair rate of the ith unit respectively and LT is known as system lead time (Billinton and Allan, 1996; Billinton and Fotuhi-Firuzabad, 1994, 2000; Guangbin and Billinton, 1994). The lead time is the time period in which no additional unit can be brought in to operation (Khan and Billinton, 1993). The system lead time is fixed at 4 h as performed in refs. (Chandrasekaran and Simon, 2012; Jalilzadeh et al., 2009; Khan and Billinton, 1993; Simopoulos et al., 2006). The repair rate, μ_i, is calculated as $\mu_i = 1/\text{RT}$. The unavailability U_{un_i} of the units is used for calculation of the cumulative probabilities by capacity outage probability tables. The cumulative probabilities are used for calculation of the LOLP index. The methodology is described in the following section.

3.2.1. Method for probabilistic assessment of generating capacities unavailability

A probabilistic unavailability evaluation method as function of the unit commitment schedule is developed. A unique characteristic of the method is that it takes into account the design characteristics of the generating units. The thermal power units in the system are separated in three categories: base load units, intermediate load units and peak load units. The classification for the units is done based on the size of the unit, start-up and shut-down times and fuel cost efficiency.

1. The base load units are considered to be on-line during all of the time intervals (hours) from the scheduling time period which is in compliance with the “must run units” constraint. Their unavailability, U_{un_i}, is calculated by Eq. (14).
2. The intermediate load units, as described above, are considered unavailable during the time intervals in which they are decommitted, i.e. if not scheduled for operation in given time interval they will be considered “as same as in outage”. Thus when decommitted their unavailability, U_{un_i}, is considered to be equal to one. These units will be considered again for supplying the load, after they become ready to generate, i.e. committed again. When committed their unavailability, U_{un_i}, is calculated with Eq. (14). The commitment of the intermediate load units and the time interval in which decommitted units can become available for generation is significantly influencing the UC unavailability.
3. The peak load units (e.g. gas-fired units) are capable to start, synchronize and accept load in a few minutes. These units are considered as operating reserve together with the spinning reserve. Considering their short start-up time, the peak load units regardless of their current state, whether on or off, will be considered available (with their calculated U_{un_i} values) during whole scheduling period. For simplification, the unavailability, U_{un_i}, of the peak load units is also calculated with Eq. (14) using the two state model not considering states such as failure to start.

This classification helps into the consideration of the inertia of the specific generating units and allows more comprehensive hour-to-hour scheduling analyses from the aspect of probabilistic unavailability assessment.

The loss of load probability is used as unavailability criterion (index), i.e. as measure for the generating capacities unavailability. In this paper the LOLP is calculated (Guangbin and Billinton, 1994; Stoll, 1989; Volkanovski et al., 2008) as follows:

$$LOLP = \sum_{t=1}^{T} cp_t(P_{C_t} < P_{L_t})\ \text{h/day} \tag{15}$$

where P_{C_t} is the committed capacity including the peak load units at hour t and cp_t is the cumulative probability calculated for a given unit commitment at hour t. The commitment capacity, P_{C_t}, is a function of the UC and is calculated as sum of the maximum power outputs of all committed units plus the maximum power outputs of all peak load units either committed or decommitted at hour t. The committed capacity, P_{C_t}, is changing given the unit commitment on hourly basis. Thus the load demand, P_{L_t}, is not the only parameter that is changing from hour-to-hour.

At each time point a unit may be committed or decommitted. The number and type of the units which are committed/decommitted may significantly influence system unavailability. The generating capacities unavailability, i.e. the LOLP, quantifies the possibility that a given load level will not be supplied by the committed generating units during the scheduling period. Therefore the generating capacities unavailability index is evaluated by convolution of the generating capacities and the load profile. The method applied in this paper is described with the following steps:

Step 1: Each committed unit at hour t is represented with its unavailability value, U_{un_i}, for a give UC schedule. The unit is considered unavailable if it is decommitted in the tth hour. Exception of the last rule is made for the peak load units as explained in the unit classification above.
Step 2: Capacity outage probability table is formed given the unit commitment schedule for the tth hour. An example of capacity outage probability table is given in Appendix B.
Step 3: Given the load level at tth hour the corresponding unavailability level, i.e. the corresponding cumulative probability, cp_t, is selected;
Step 4: The procedures according to Step 2 and Step 3 are repeated for all of the time intervals from the scheduling time period, T;
Step 5: The unavailability of generation capacities, F_U, is calculated using Eq. (15), i.e. $F_U = LOLP$.

Fig. 1 shows a schematic flowchart of performing steps 2–4.

The LOLP is not the only unavailability measure that can be used as an estimate for the unavailability of the generating capacities. Another unavailability measure that can be used is the EENS.

3.2.2. *Capacity outage probability tables*

Capacity outage probability tables are basically two-dimensional matrices comprising the capacity levels, or the corresponding capacities being out of service as well as the associated probabilities of their occurrence (Billinton and Allan, 1992, 1996). These probabilities of occurrence are defined as the probability that the indicated capacity amount will be out of service. Usually, the cumulative probability of occurrence is applied for the capacity modelling. This cumulative probability is defined as the sum of probabilities corresponding to capacity being in outage equal to or greater than the indicated amount. Capacity outage probability tables can be created using a convolution algorithm (Billinton and Allan, 1992, 1996; Volkanovski et al., 2008).

3.2.3. *Deterministic reserve evaluation*

The standard way of designating a specific power system reserve is by applying a deterministically assessed value as a criterion to be

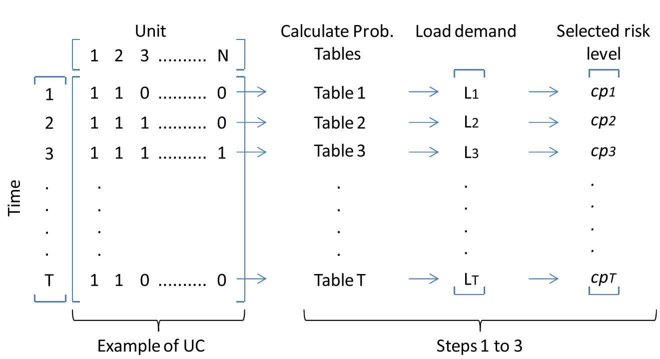

Fig. 1. A schematic representation of the probabilistic unavailability assessment technique.

met. This value is usually set to equal to the largest generating capacity or some percentage of the peak load (Billinton and Allan, 1996; Bouffard and Galiana, 2004). Two scenarios are analysed regarding the spinning reserve: one scenario where a minimum margin of 10% spinning reserves from the load demand is required at each time interval and another scenario where no margin is considered at all. However, since the trade-off between the total cost and unavailability of generation capacities are analysed in this study, multiple unit commitment solutions are obtained. Each of these unit commitment solutions results with different spinning reserves for each time interval. In order to explore the trade-off between the total cost and the spinning reserves simple deterministic model is constructed as function of the spinning reserve. First, the hourly spinning reserves are calculated as follows:

$$R_t = \sum_{i=1}^{N} R_{i,t} \tag{16}$$

where $R_{i,t}$ is the spinning reserve contributed by the ith unit at the tth hour, i.e. the spinning reserve $R_{t,i}$ is calculated as difference between the maximum power output of the ith unit and the power output that this unit has at hour t ($R_{i,t} = P_{G_i}^{max} - P_{G_{i,t}}$). Then, the spinning reserve index is formed as follows:

$$F_R = \frac{T}{\sum_{t=1}^{T} R_t} \tag{17}$$

This model is applied on the entire unit commitment solutions set obtained using the unavailability assessment model and the results are subsequently compared. The spinning reserve index is introduced only for comparative purpose.

4. Problem formulation

Both objective functions, the cost function given with Eq. (1) and the generation unavailability function given with Eq. (15), are evaluated separately. Subsequently, the combined unavailability–economic UC is evaluated and described as follows:

$$\text{Minimize}\ [F_T(S, P_G), F_U(S, P_G)] \tag{18}$$

subject to:

$$g(S, P_G) = 0 \tag{19}$$

$$h(S, P_G) \le 0 \tag{20}$$

where $g(S,P_G)$ and $h(S,P_G)$ are the equality and inequality problem constraints, respectively, S is the commitment status of the units, and P_G is a decision matrix that represents potential solution. Since the UC is a mixed-inter problem which comprises two interconnected optimization sub-problems, the integer-valued unit commitment schedule and the real-valued generation dispatch, the decision space is represented as follows:

$$S, P_G = \begin{bmatrix} S_{1,1}, P_{G_{1,1}} & S_{1,2}, P_{G_{1,2}} & \cdots & S_{1,t}, P_{G_{1,t}} & S_{1,T}, P_{G_{1,T}} \\ \vdots & & & \ddots & \vdots \\ S_{i,1}, P_{G_{i,1}} & S_{i,2}, P_{G_{i,2}} & \cdots & S_{i,t}, P_{G_{i,t}} & S_{i,T}, P_{G_{i,T}} \\ \vdots & & & \ddots & \vdots \\ S_{N,1}, P_{G_{N,1}} & S_{N,2}, P_{G_{N,2}} & \cdots & S_{N,t}, P_{G_{N,t}} & S_{N,T} P_{N,T} \end{bmatrix} \tag{21}$$

The number of rows, N, is equal to the number of generating units and the number of columns, T, is equal to the number of time intervals. When solving the UC problems two types of decision variables are determined, the units on/off status variables, $S_{i,t}$, and the units power outputs variables, $P_{i,t}$.

5. Problem solution

To solve the UC problem, as single objective and multi-objective problem, a real-coded genetic algorithm was constructed. The GA was also used for the generation (economic) dispatch of the committed units in the system. Similar approach were binary-real-coded GA is used to solve both, the UC schedule and the generation dispatch is shown in Ref. Datta (2013). The binary-coded GA is used for the UC schedule while the real-coded GA is used for the generation dispatch. The main difference between the approach from Ref. Datta (2013) and the approach used in this study is that the latter uses real coded GA for both sub-problems with different types of reproduction mechanisms for each sub-problem.

In order to improve the performance of the used GA a hybrid methodology which comprises priority list was used. Additionally, the algorithm comprises mechanisms for constraint violations repairs.

5.1. Algorithm description

The algorithm procedure is presented within the continuation of this section.

5.1.1. Priority list

First, all the power plants are divided in separate groups: must-run group (base load units), intermediate group (intermediate load units), peak group (peak load units). The groups are arranged starting from the must-run group, the intermediate group and the peak group. Next, the plants in all groups are ranked in ascending order of the best heat rate (Saber et al., 2007). In such a way a priority list is formed. Consequently, units are being committed given their rank. For each time interval the most economic unit is committed first, the procedure continues until the load demand including the spinning reserves are satisfied. There is a possibility that some of the most expensive units are not committed at all.

5.1.2. Initial population

In general, when GA is used for optimization purposes, the initial population is generated randomly. The solution obtained using the priority list is used as initial solution instead of totally random generated population. However, some solutions are still generated at random. Therefore, the initial population contains three groups of solutions: random solutions, priority list solutions and hybrid solutions. Each potential solution from the population is represented with matrix as shown with Eq. (21).

5.1.2.1. Random solutions. These solutions are created such that all units are committed at the beginning. Then, a random decommitment is performed with predefined probability. However, in order to satisfy the must-run constraint all base-load units are set as committed at all intervals. After the UC is defined the committed generators are assigned with their output power, $P_{G_{i,t}}$, which are generated at random in the interval: $P_{G_i}^{min} \le P_{G_{i,t}} \le P_{G_i}^{max}$. The generator output values are used for the generation dispatch problem which is solved simultaneously.

5.1.2.2. Priority list solutions. The obtained UC solution using the priority list is also used as such in the initial population, i.e. a chosen number of solutions are randomly placed in the initial population. These solutions are of value for the GA because they provide additional information in the GA search space (Orero and Irving, 1997; Todorovski and Rajicic, 2006). If enough elitism is applied in the GA, the worst solutions that can come out of it are the priority list solutions.

5.1.2.3. Hybrid solutions. The philosophy behind the hybrid solutions is that they are using the priority list solutions as a starting point. First, a predefined search rate, s_r, is used in order to track an amount of generating units in the base load solution. This amount is calculated as: $NS = N^*T^*s_r$. In other words NS gives the number of generating units in the priority list solution that will be randomly chosen and afterwards replaced. A pseudo-code description of the procedure is given as follows:

```
set counter to i = 0
while i < NS
    i = i + 1
    choose a variable, S_{i,t}, at random
    if S_{i,t} belongs to a base load unit
        replace P_{G_{i,t}} with new variable generated at
  random in the interval P_{G_i}^{min} ≤ P_{G_{i,t}} ≤ P_{G_i}^{max}
else if S_{i,t} = 1 (committed)
        set S_{i,t} = 0 (decommitment) and P_{G_{i,t}} = 0
else If S_{i,t} = 0 (decommitted)
        set S_{i,t} = 1 (commitment) and generated P_{G_{i,t}} at
  random in the interval
        P_{G_i}^{min} ≤ P_{G_{i,t}} ≤ P_{G_i}^{max}
    end
end
```

The procedure is repeated until the predefined number of hybrid solutions is created. The algorithm is set such that the number of hybrid solutions is dominating in the initial population. The employment of the hybrid solutions in the initial population is main improvement performed on the classical hybrid GA.

5.1.3. Repair mechanisms

Once the initial population is created it is very difficult to generate solutions that satisfy all equality and inequality system and unit constraints, especially when random generated variables are introduced. In order to improve the initial solution properties in direction of satisfying the constraints, i.e. reappearing procedures are introduced. The reappearing procedures are adopted from (Senthil Kumar and Mohan, 2010; Sun et al., 2006). The objective of the repair mechanism is to repair the solutions that are infeasible regarding given constraint (minimum up and down time constraints, Eq. (11), and system spinning reserves constraints, Eq. (12)).

The repair procedure for the up and down time constraints is applied if a unit in a given solution violates the up or down time constraints. The commitment state of the unit is evaluated starting from the begging of the scheduling period. If at hour "*t*" the unit violates the minimum up time constraint the unit state is updated committing the unit in the following hours until the constraint is satisfied. If the minimum down time constraint is violated at hour "*t*" the unit state is updated committing the unit in the off hours between two committed states. Similar procedure is used for the system spinning reserve constraints with that difference that the evaluation is performed per hour instead per unit. If in a given hour "*t*" the constraint is violated, which means not enough spinning reserves are provided, the next most efficient decommitted unit in the system is committed. The commitment of the next most efficient unit continues until the constraint is satisfied.

These procedures are not used only after the initial population is generated, but also after crossover and mutation operators are applied. The rest of the constraints are dealt with when the generation dispatch is solved for the obtained feasible solutions as presented in following subsections.

5.1.4. Fitness function

The fitness function consolidates all objectives as well as the penalty term (Gjorgiev et al., 2013) as follows:

$$f = wF_T^n + (1-w)F_U^n + \delta_d \sum_{m=1}^{NC} VIOL_m \tag{22}$$

where f stands for objective function, w is the weighting factor, F_T^n and F_U^n are the normalized values of the objectives functions F_T and F_U respectively, δ_d is the penalty parameter, $\sum_{m=1}^{NC} VIOL_m$ denotes the penalty term, $VIOL_m$ is the constraint violation and NC is the number of constraints involved. The constraints dealt with within this phase are the power balance constraints, Eq. (5), and operating ramp rate constraints, Eqs. (7) and (8).

As seen from Eq. (22) the weighted sum method is applied to deal with the multi-objective optimization problem within this paper (Gjorgiev et al., 2013). The weighting factor, w, from Eq. (22) has values selected in the range between 0 and 1.

Similar application of the weighted sum method for solving the combined economic–environmental UC problem is presented in Chandrasekaran et al. (2012). The weighted sum method also extends its application for solving problems such as the profit based unit commitment (Ahmadi et al., 2012).

5.1.5. Selection

The main idea behind the selection procedure is identification of solutions, designated as parents which are fit to reproduce. In turn, offspring population will be gained out of this reproduction. The tournament selection approach (Goldberg and Deb, 1991) is applied herein. This selection technique suggests random selection of two or more solutions at a time and their comparison based on their fitness values. The solution with best fitness wins the tournament, i.e. is being designated as a parent and placed in the mating pool. In such a way, the selection is being reapplied until the mating pool is filled. Tournament size of two is used for all the analysis within this paper.

5.1.6. Crossover

The very act of reproducing, i.e. combining two or more solutions selected to be parents implying creation of two or more offspring, is being performed by the crossover operator. The crossover used in this paper has two segments, one for the unit commitment states and one for the generator power outputs. The procedure for the first segment is as follow:

select multiple points at each row from the parent chromosomes
if $S_{i,t}$ (chromosome 1)=0 and $S_{i,t}$ (chromosome 2)=0
    perform no operation
else
    swap variables ($S_{i,t}$, $P_{G_{i,t}}$)
end

This procedure is applied on each pair of parent chromosomes selected for crossover. The first segment does not introduce sufficiently valuable information for the generation dispatch problem since is only swapping the information between the selected chromosomes. Therefore, the second segment is applied. Randomly chosen variable from the first chromosome is selected and swapped with the variable with same position (column, row) in the second chromosome, applying the blend crossover (BLX-α) (Eshelman and Schaffer, 1993). The pseudo-code of the applied crossover operator is as follows:

select multiple points at each row from the parent chromosomes
if a $S_{i,t}$ (chromosome 1)=1 and $S_{i,t}$ (chromosome 2)=1
    swap variables performing the BLX-α
end

The procedure above applied on each pair of parent chromosomes selected for crossover.

5.1.7. Mutation

The mutation operator is applied so the diversity of the population will be sustained as an important factor which leads the search towards global optima. The mutation operator also has two segments, one for the unit commitment states and one for the generator power outputs. The procedure for the first segment is as follow:

choose a variable, $S_{i,t}$, at random
if $S_{i,t}$ belongs to a base load unit
    do not perform any operation
else if $S_{i,t}$=1 (committed)
    set $S_{i,t}$=0 (decommitment) and $P_{G_{i,t}}=0$
else
    set $S_{i,t}$=1 (committmend) and generated $P_{G_{i,t}}$ at random in the interval $P_{G_i}^{min} \le P_{G_{i,t}} \le P_{G_i}^{max}$
end

In the next stage the second segment is applied. The non-uniform mutation procedure (Michalewicz, 1996) is implemented with a static mutation rate. Each chromosome is separately processed. The unit commitment states are also taken in to consideration as follows:

randomly select variable for mutation, $S_{i,t}$
if $S_{i,t}$=1
    perform non-uniform mutation ($P_{G_{i,t}} = P_{G_{i,t}}^{new}$)
end

5.1.8. Replacement

An elitist type of replacement technique is being applied in this study (Gjorgiev and Čepin, 2013). The technique is based on a comparison among the parent and their offspring chromosomes. Each pair of parent chromosomes and their corresponding offspring chromosomes are placed in subgroups, each of which comprises four chromosomes. Namely, parent pairs are compared to the corresponding offspring chromosomes, in a way that only two survive. These surviving chromosomes from each subgroup define the new generation, i.e. the GA enters the next iteration of its cycle.

5.2. Algorithm application

As mentioned before, the UC problem is separately solved as single objective and as a multi-objective. When solved as a single objective problem, both the total cost, F_T, and the unavailability of generation capacities, F_U, are minimized separately. When solved as a multi-objective optimization problem, both objective functions are simultaneously minimized. Therefore, different algorithm properties are selected and also different methodologies for the generation of the initial population are applied.

When the UC problem is solved as single objective two concepts for creation of the initial population are used:

1. *Total cost, F_T, as single objective*: The population is generated as explained in Sections 5.1.1 and 5.1.2. In this case the used priority list is based on the fuel cost.

2. *Unavailability of generation capacities*, F_U, *as single objective*: The conventional priority list, based on fuel cost, is not used. Instead the priority list is based on the generation capacities unavailability. This priority list is produced such that all base load and intermediate load units are set to be continuously committed while the peak load units are committed or decommitted such that the load demands and spinning reserves are satisfied at each time interval. This solution is further used for creation of the initial population using the same analogy as described in Section 5.1.2.

When the UC problem is solved as multi-objective optimization problem the initial population is formed by solutions created using both concepts described above. The portion of each type of solutions is proportional on the value of the weighted factor, w, defined within Eq. (22). For example if $w=1$ the unavailability part of the equation is discarded. The multi-objective optimization problem is reduced to a single objective optimization problem with cost minimization as solo objective. In this case the initial solutions are created using the first concept from above. In case of $w=1$ the cost part of the equation is discarded. The multi-objective optimization problem is reduced to a single objective optimization problem with unavailability minimization as solo objective. In this case the initial solutions are created using the second concept from above. In case of $w=0.5$ (equal priority given to both objectives) the initial population is composed from equal portions of solutions created using both concepts from above.

The algorithm capability to deal with the UC problem is presented in Appendix A.

6. Analyses and results

The algorithm used in this study has been coded in MATLAB 7.7 environment and implemented on Intel(R) Core(TM) i5 CPU. The parameters of the applied GAs are set by applying the trial and error approach. Each of the GAs used for each of the above defined sub-problems was run several times with different set of parameters such as the number of generations, population size, crossover rate and mutation rate. The algorithms were also tested on different optimization problems. The sets of parameters giving the most promising results were selected.

The 10-unit thermal power system considered in the analyses is adopted from Kazarlis et al. (1996) while the ramp rate limits are adopted from Yamashita et al. (2010). This is a common benchmark power system commonly used in the scientific literature. The default unit data does not consider the valve load effects and prohibited operating zones constraint, thus they are not included in the calculations. Other system component and phenomena such as the transmission network constraints, power losses and load forecast uncertainties are not considered in the study as well. Table 1 shows the relevant failure rates, repair time and the calculated unavailability of each generating unit.

The failure rates and the repair times for the generating units are extrapolated from the data given in Billinton and Allan (1996), where the outage rate is presented as a function of the unit size. The unit unavailability, U_{un_i}, is calculate using Eq. (14). System lead time of 4 h is selected as performed in Khan and Billinton (1993) and Simopoulos et al. (2006), where the effect of the lead time on the LOLP was investigated.

Two analyses scenarios are performed for the test power system. In the first scenario a low margin for the spinning reserves of 10% from the load demands at each hour is selected, i.e. the system reserve requirements constraint given with Eq. (12) are considered. In the second scenario no margin for the spinning reserves is selected, i.e. the planning of the reserves is not taken in to consideration.

6.1. *Scenario 1*

For scenario 1 the UC problem is solved as single objective, i.e. the total cost and unavailability of generation capacities are minimized independently. The obtained UC schedules are presented in Tables 2 and 3 respectively. The UC problem is also solved as a multi-objective optimization problem considering both of the objectives simultaneously. Table 4 represents the best compromise solution (BCS). This solution is obtained when equal priority is assigned to both of the objective functions, i.e. the weighting factor, w, is selected to be 0.5.

By comparing the UC schedules from Tables 2 and 3 it is apparent that the main difference is the scheduling of the intermediate load units. In the first case they are scheduled only when needed which results with improved economy, while as in the

Table 1
Relevant probability data for the test power system.

P (MW)	455	455	130	130	162	80	85	55	55	55
λ (f/yr)	13.5	13.5	6.17	6.17	6.11	4.37	4.88	3.41	3.41	3.41
RT (h)	80	80	55	55	55	50	50	40	40	40
U_{un_i} (dimensionless)	0.00599	0.00599	0.00271	0.00271	0.00269	0.00192	0.00214	0.00148	0.00148	0.00148
FOR (dimensionless)	0.10976	0.10976	0.03729	0.03729	0.03694	0.02434	0.02710	0.01533	0.01533	0.01533

Table 2
UC scheduling for total cost minimization.

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

Table 3
UC schedule for the generation capacities unavailability minimization.

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

Table 4
UC schedule for the BCS.

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

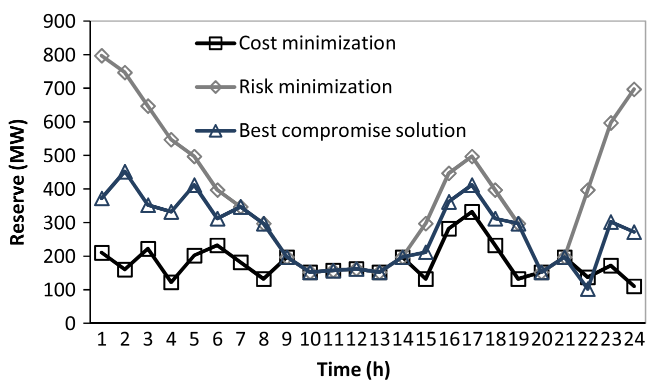

Fig. 2. Cost vs. unavailability minimization, scenario 1: Reserve schedule.

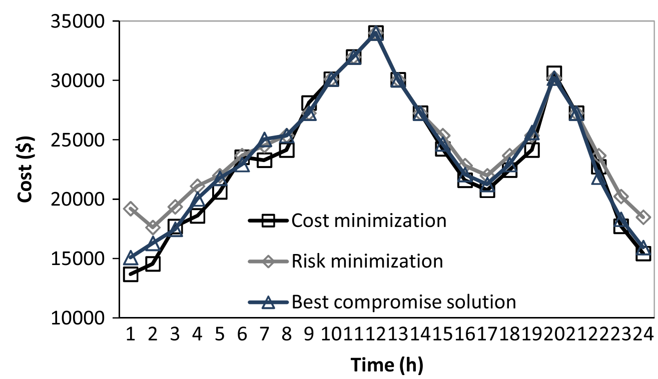

Fig. 4. Cost vs. unavailability minimization, scenario 1: Operating cost at each hour.

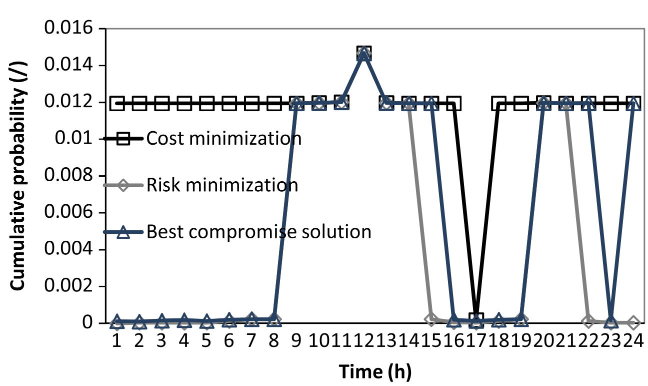

Fig. 3. Cost vs. unavailability minimization, scenario 1: Cumulative probability at each hour.

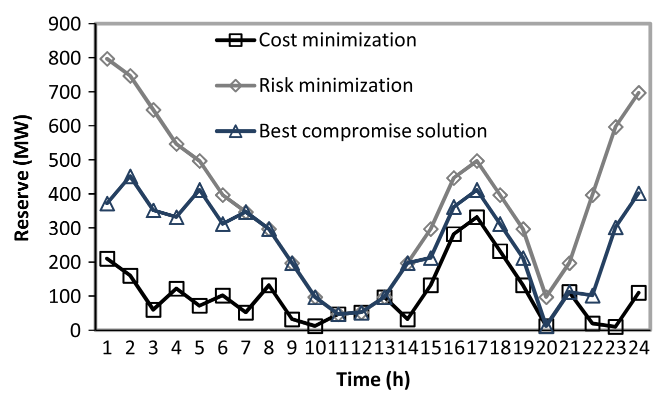

Fig. 5. Cost vs. unavailability minimization, scenario 2: Reserve schedule.

second case they are scheduled during the entire scheduling period which results with improved generating capacities availability. A compromise between both objectives, cost and unavailability, is achieved by appointing a BCS solution given in Table 4. This is inevitably related with the scheduling of the spinning reserves, R_t, as shown with Fig. 2.

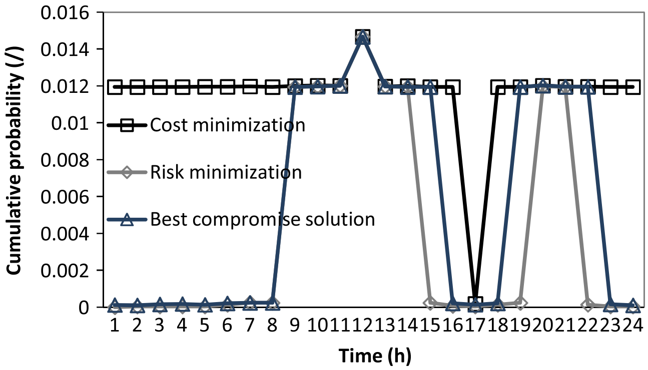

Fig. 6. Cost vs. unavailability minimization, scenario 2: Cumulative probability at each hour.

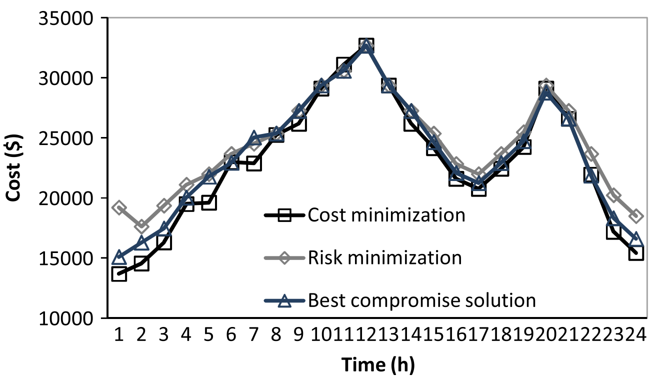

Fig. 7. Cost vs. unavailability minimization, scenario 2: Operating cost at each hour.

Fig. 2 shows the available spinning reserves at each consecutive hour in the range of 0–24 h for all three cases: cost minimization solely, unavailability minimization solely and simultaneous minimization of both unavailability and cost, i.e. multi-objective optimization problem with a BCS as a representative solution. It is obvious that higher reserves correspond to higher cost and lower unavailability.

Additionally, a comparison is made for the obtained cumulative probabilities, cp_t, and operational cost, F_t, for all three solutions (Figs. 3 and 4).

6.2. Scenario 2

The same procedure from above is followed for this scenario with a single difference that the reserve requirements constraint given with Eq. (12) is not considered. Figs. 5–7 show the reserve schedule, cumulative probability at each hour and operating cost at each hour respectively.

6.3. Scenario 1 vs. Scenario 2

Fig. 8 illustrates the obtained Pareto fronts for both scenarios when the UC problem is solved as a multi-objective optimization problem, while Table 5 summarizes all of the results from both scenarios. For comparative purposes the spinning reserves are estimated for each of the obtained optimal UC schedules in both scenarios and the spinning reserve deterministic index is calculated according to Eq. (17). The result is a Pareto front for each of the scenarios as shown in Fig. 9.

Fig. 8 shows that there are very small differences in the unavailability levels between scenario 1 and scenario 2. However there is some substantial difference in the cost mainly for the solutions where the cost objective is prioritized. A detailed discussion for the meaning of the results is given in the following section.

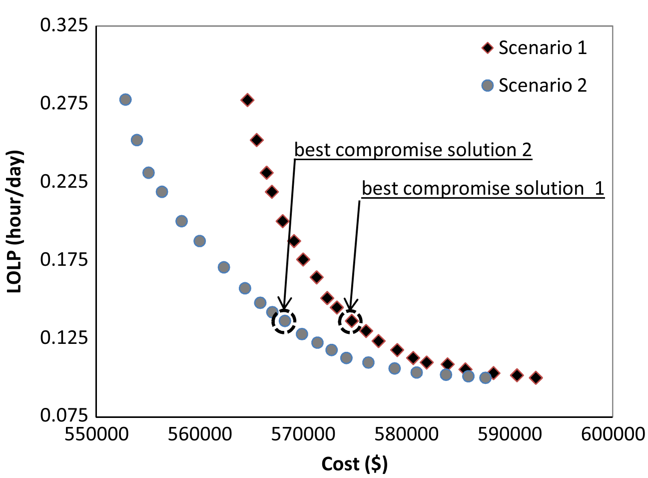

Fig. 8. Pareto fronts for scenario 1 and scenario 2; probabilistic evaluation.

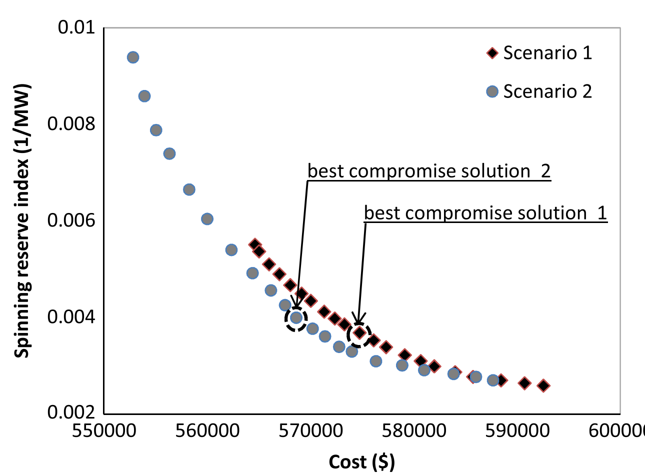

Fig. 9. Pareto fronts for scenario 1 and scenario 2; deterministic evaluation.

Table 5
Summary of the results for 10-units test system.

	Scenario 1			Scenario 2		
	min[F_T]	min[F_U]	min[F_T, F_U] BCS	min[F_T]	min[F_U]	min[F_T, F_U] BCS
Cost ($)	564,405	592,544	574,724	552,815	587,662	568,249
LOLP (h/day)	0.2778	0.1001	0.1365	0.2781	0.1001	0.1365
Spinning reserves average (MW)	181.54	386.17	271.38	106.5	370.125	250.12
CPU (s)	4.09	17.48	361.44	3.94	17.32	359.67

Table 6
Summary of the results for 12-units test system.

	Scenario 1			Scenario 2		
	min[F_T]	min[F_U]	min[F_T, F_U] BCS	min[F_T]	min[F_U]	min[F_T, F_U] BCS
Cost ($)	610,023	638,027	620,145	598,228	633,142	614,240
LOLP (h/day)	0.0515	0.0345	0.0379	0.1851	0.0345	0.0498
Spinning reserves average (MW)	181.54	386.17	271.38	106.5	370.125	250.12
CPU (s)	4.12	18.21	367.01	4.03	17.64	364.20

Fig. 9 shows that the obtained results in scenarios 1 and 2 are very similar. The main difference is that the solutions from scenario 2 are stretching wider on the cost axis. This is expected, since in scenario 2 no margin for the spinning reserves exists, therefore lower costs can be obtained. The results shown in Fig. 9 are given only to illustrate the difference between the deterministic and the probabilistic approach. It is clear that the obtained results presented with Fig. 9 do not give any estimate about unavailability, which is not the case with Fig. 8. Using the proposed method not only a probabilistic evaluation but also deterministic estimates can be made easily.

6.4. Discussion

Fig. 8 and Table 5 shows that generation capacities unavailability, i.e. LOLP improvements can be made with proper scheduling of the intermediate load units. The obtained trade-off between the total operating cost and generation unavailability can be used from the decision maker to derive the solution with the most significance.

However, as it is shown in Fig. 8 and Table 5, even in the best case the unavailability index is relatively high. The reason for this is the composition of the power system, i.e. two 455 MW units are installed and they produce most of the energy during one day. However, these units have quite high failure rates which implicate their relatively high unavailability. If failure of even one of the units occurs, there will not be any reserves to replace it for the most of the hours of the day even if all units are scheduled for operation. The general conclusion is that this system has been poorly composed during the planning phase.

Another important note is that there is almost no difference in the LOLPs obtained in scenario 1 and scenario 2. Same as discussed above, the failure of one of the most unreliable units which in the same time are the units with the highest capacity means that no operating reserves will be available to cover for the load demands for the most of the hours during the scheduling time period. Therefore, it is not of a great significance if a 10% reserve margin exists in scenario 1 compared to scenario 2 where no predefined margin is used.

A simple experiment has been conducted here. Each of the two major units with 455 MW is replaced with two 227.5 MW units. The unavailability value of 0.00377 is applied for both units, while the cost characteristics of the units remain the same. This change adapts the 10-units power system to a 12-units power system. The proposed method for calculation of generating capacities unavailability is applied on this system. The obtained results are presented in Table 6.

By comparing the results presented in Tables 5 and 6 one can conclude that the proposed change significantly reduces the unavailability of the test power system. Another important note is that in the case with the 12-units test system a significant difference exists between the LOLPs obtained in scenario 1 and scenario 2. The pre-defined 10% reserve margin has a significant influence on the LOLP which was not the case for the 10-units test system. This is due to the fact that the scheduled spinning reserves for the 12-unit test system can cover for the loss of the largest generating unit for most of the time intervals. A conclusion can be derived that the design and operating phase of a power system are inherently connected.

This is an example for the applicability of the developed method not only for the short-term generation scheduling but also for long term power system planning.

7. Conclusions

This study addresses the problem of unit commitment and its consideration within the unavailability profile of a specific power system. A new methodology for probabilistic assessment of generating capacities availability and its incorporation within the unit commitment issue is proposed. The unit commitment is related to the action of adequate planning of the reserve capacities. This paper presents a probabilistic unavailability evaluation method as function of the unit commitment schedule, which is dynamic in its nature. The loss of load probability is considered as the relevant unavailability measure and is evaluated by convolution of the generating capacities and the load profile. In such way, an option to account and delineate among the rapid-starting and slow-starting units and, consequently, to implement the implications on the total unavailability profile is accommodated by this methodology. The unavailability of each individual unit is calculated using the two-state model. A scheduling period of 24 equi-lasting time intervals of 1 h is considered.

A multi-objective optimization problem defined within a selected case study power system is presented and solved. Two objective functions, a generation cost function and unavailability of generating capacity function, i.e. LOLP, are being considered. An improved hybrid genetic algorithm technique is selected as the optimization tool. Two scenarios are analysed. First one with a low margin for the spinning reserves and a second one with no margin at all are of interest. The thermal power units in the system are separated in three categories: base load units, intermediate load units (slow-starting) and peak load units (rapid-starting).

The results show a detailed picture of the interdependence between unavailability and cost as a function of the given objective priority. Moreover, the results of the analyses show that generation capacities unavailability improvements can be made with proper scheduling of the intermediate load units. Also, using this method not only a probabilistic evaluation but also deterministic estimates can be made easily. Given the presented test power system it is shown that choosing not to consider the reserve constraint rather than considering a fixed value for this constraint implicates with major economic consequences rather than unavailability implications. This was not the case after the proposed improvement of the test power system was considered.

The need for consideration of the generation capacities unavailability in to the unit commitment problem for short-term scheduling purposes in order to obtain more detailed unavailability models is supported by the obtained results. Consequently, more detailed power system unavailability profile can be obtained and analysed with the developed method.

Acknowledgements

The Slovenian Research Agency supported this research (research programme P2-0026).

Appendix A. Algorithm validation

In order to verify the capability of used algorithm to solve the UC problem the algorithm is applied on a 10, 20, 40, 60, 80 and 100 unit test system. The 20-units system is made duplicating the 10-units system, the load demands are duplicated also. The same procedure is applied for all of the other studied systems. The 10-unit thermal power system considered in the analyses is adopted from Kazarlis et al. (1996) while the ramp rate limits are adopted from Yamashita et al. (2010). Most of the other studies with which the comparison is made do not consider the ramp rate constraint. The algorithm is run 10 times for each test system. The obtained results are compared with the one available in the literature as shown in Table A1.

According to the results given in Table A1 it can be concluded that the proposed algorithm generates good and reliable solutions. The results also show that there is no substantial difference between the best and worst solutions obtained with the proposed algorithm. This demonstrates the algorithm capability to find reliable solutions. The algorithm also showed good calculation times which for some of the performed calculations are presented previously in the text. Table A2 depicts the output generation of each commitment unit at each time obtained for the 10-units system using the proposed algorithm.

Table A1
Cost ($) comparison between the proposed and other algorithms.

[a]Units	LR (Kazarlis et al., 1996)	EP (Juste et al., 1999) average	ICGA (Damousis et al., 2004) average	AG (Cheng et al., 2002)/	BCGA (Kazarlis et al., 1996)		GA (Senjyu et al., 2002)		NSGA-II (Yan-Fu et al., 2013)		Proposed algorithm	
					Best	Worst	Best	Worst	Best	Worst	Best	Worst
10	565,825	565,352	566,404	564,005	565,825	570,032	563,977	565,606	563,938	564,723	564,405	564,797
20	1,130,660	1,127,257	1,127,244	1,124,651	1,126,243	1,132,059	1,125,516	1,128,790	–	–	1,126,290	1,127,715
40	2,238,503	2,252,612	2,254,123	2,249,072	2,251,911	2,259,706	2,249,715	2,256,824	–	–	2,250,823	2,254,312
60	3,394,066	3,376,255	3,378,108	–	3,376,625	3,384,252	3,375,065	3,382,886	–	–	3,376,056	3,381,846
80	4,526,022	4,505,536	4,498,943	–	4,504,933	4,510,129	4,505,614	4,527,847	–	–	4,505,217	4,512,872
100	5,657,277	5,633,800	5,630,838	–	5,627,437	5,637,914	5,626,514	5,646,529	5,605,918	5,617,595	5,627,431	5,636,284

[a] LR – Lagrange relaxation; EP – Evolutionary programming; ICGA – integer-coded GA; AG – Annealing – Genetic algorithm; NSGAII – Non-dominated sorting GA-II; BCGA – binary coded GA.

Table A2
Generator output schedule (MW), load demand (MW) and fuel costs ($) for the 10-units system.

Hour	U 1	U 2	U 3	U 4	U 5	U 6	U 7	U 8	U9	U 10	Load	Start-up cost	Fuel cost	Total cost
1	455	245	0	0	0	0	0	0	0	0	700	0	13,683	13,683
2	455	295	0	0	0	0	0	0	0	0	750	0	14,554	14,554
3	455	370	0	0	25	0	0	0	0	0	850	900	16,809	17,709
4	455	455	0	0	40	0	0	0	0	0	950	0	18,598	18,598
5	455	455	0	65	25	0	0	0	0	0	1000	560	20,060	20,620
6	455	455	35	130	25	0	0	0	0	0	1100	1100	22,442	23,542
7	455	455	85	130	25	0	0	0	0	0	1150	0	23,284	23,284
8	455	455	130	130	30	0	0	0	0	0	1200	0	24,150	24,150
9	455	455	130	130	85	20	25	0	0	0	1300	860	27,251	28,111
10	455	455	130	130	162	33	25	10	0	0	1400	60	30,058	30,118
11	455	455	130	130	162	73	25	10	10	0	1450	60	31,916	31,976
12	455	455	130	130	162	80	58	10	10	10	1500	60	33,945	34,005
13	455	455	130	130	162	33	25	10	0	0	1400	0	30,058	30,058
14	455	455	130	130	85	20	25	0	0	0	1300	0	27,251	27,251
15	455	455	100	130	60	0	0	0	0	0	1200	0	24,150	24,150
16	455	455	20	95	25	0	0	0	0	0	1050	0	21,598	21,598
17	455	455	20	45	25	0	0	0	0	0	1000	0	20,758	20,758
18	455	455	35	125	30	0	0	0	0	0	1100	0	22,442	22,442
19	455	455	130	130	30	0	0	0	0	0	1200	0	24,150	24,150
20	455	455	130	130	130	65	25	10	0	0	1400	490	30,058	30,548
21	455	455	130	130	85	20	25	0	0	0	1300	0	27,251	27,251
22	455	455	0	0	145	20	25	0	0	0	1100	0	22,736	22,736
23	455	400	0	0	45	0	0	0	0	0	900	0	17,685	17,685
24	455	345	0	0	0	0	0	0	0	0	800	0	15,427	15,427
Sum of costs												4090	563,015	564,405

Table B1
Capacity outage probability table for the froth hour of the UC schedule for the minimum cost solution.

Capacity state	Capacity service		Probabilities	
	Out (MW)	In (MW)	Individual	Cumulative
1	0	1237	7.2839E−01	1.0000E+00
2	55	1182	3.3953E−02	2.7161E−01
3	110	1127	5.2754E−04	2.3766E−01
4	162	1075	2.7907E−02	2.3713E−01
5	165	1072	2.7323E−06	2.0922E−01
6	217	1020	1.3008E−03	2.0922E−01
7	272	965	2.0212E−05	2.0792E−01
8	327	910	1.0468E−07	2.0790E−01
9	455	782	1.8005E−01	2.0790E−01
10	510	727	8.3928E−03	2.7849E−02
11	565	672	1.3040E−04	1.9456E−02
12	617	620	6.8984E−03	1.9326E−02
13	620	617	6.7540E−07	1.2427E−02
14	672	565	3.2156E−04	1.2427E−02
15	727	510	4.9963E−06	1.2105E−02
16	782	455	2.5877E−08	1.2100E−02
17	910	327	1.1127E−02	1.2100E−02
18	965	272	5.1865E−04	9.7324E−04
19	1020	217	8.0587E−06	4.5459E−04
20	1072	165	4.2631E−04	4.4653E−04
21	1075	162	4.1738E−08	2.0224E−05
22	1127	110	1.9872E−05	2.0182E−05
23	1182	55	3.0876E−07	3.1036E−07
24	1237	0	1.5991E−09	1.5991E−09

Appendix B. Capacity outage probability table example

Table B1 shows an example of capacity outage probability table calculated for the froth hour of the UC schedule for the minimum cost solution (Tables 3 and A2). As Table 3 shows only three units are committed in the fourth hour, two base load units and one intermediate unit. However in the construction of the probability table the three peak load units are considered as well as the method proposed in this paper suggests. Therefore the number of units considered in the calculation of the capacity outage probability table is six. The number of possible capacity states is 24 as shown in Table B1.

The load demand in the fourth hour is 950 MW. The capacity state 7, with capacity in service of 965 MW, is assigned for this load demand. For capacity state 7 a cumulative probability of 2.0792E−1 is selected. The same procedure is applied for each hour (frame) from the 24-h scheduling period.

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