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UNIT COMMITMENT AND OPERATING RESERVE ASSESSMENT FOR RISK MANAGEMENT VIA G.A.

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ABSTRACT
An important problem in power system operation is to determine the operating reserve in order to reduce the risk of not supplying the load in consequence of contingencies. In literature the so-called well being model has been suggested to solve it. In the paper a genetic algorithm is used to overcome the computational burden due to the model complexity and to find the optimal solution. The results obtained on a test system show the effectiveness of the proposed approach.

KEY WORDS
Operating Reserve, well-being model, Genetic Algorithms, Unit Commitment, Risk Management.

1. Introduction

A power system operator must constantly assess the required spinning reserve in order to operate the system as securely and as economically as possible. Security is achieved by carrying extra operating capacity at all time to supply loads in case of unplanned events, such as unforeseen load changes, sudden generation and line outages or any other contingency which results in loss of generation capacity.

In today's electric power industry, the spinning reserve requirements are usually based on deterministic criteria. The disadvantage of this approach is that it does not take into account the occurrence probability of a contingency that actually influences the power system risk.

Conversely, usage of probabilistic techniques would permit the capture of the random nature of system components and load behaviour in a consistent manner. Despite of the obvious disadvantage of deterministic approaches, there is considerable reluctance to apply probabilistic techniques to assess the spinning reserve requirement.

Other authors have already found a compromise between the deterministic and the probabilistic methods known in literature as "system well-being" [1]. In consequence of a contingency the system may reside in health, margin or at risk state in terms of the degree to which the reliability constraints are satisfied, i.e. power not delivered to the load [1]. The probabilites associated with the different contingencies are evaluated and the system well-being indices can be calculated from these probabilities. Hence the healthy, marginal and at risk state probabilities are the probability of the composite system to be operating in the healthy, marginal and at risk states respectively.

Since system health, margin and risk probabilities are influenced by the amount and by the different type of operating reserve. Previous papers, based on the above well-being approach, have presented a mathematical framework in order to determine the reserve requirements to have an acceptable risk probability. This framework includes the computational requirements in both spinning and supplemental reserves. Non-spinning reserves, such as rapid start gas turbine units and hot reserve units, are assessed using the concepts of area risk curves, in which the respective lead times play one of the key roles in the analysis [1], [2]. The same concept is used for the interruptible load interpreted as a part of the operating reserve. The system area risk curve will then depend also on the instant and duration of interruption [3].

The goal of the present paper is to determine the optimal mix of operating reserve units (rapid start, hot reserve units, interruptible loads) in order to obtain the desired reliability degree at the minimum cost. This optimal mix is the solution of a complex mathematical optimisation problem, with integer variables. The exact solution to the problem can be obtained by complete enumeration, which cannot be applied to realistic power systems, due to the excessive computational time requirements. In order to decrease the computational time performing an appropriate searching procedure, in the paper a Genetic Algorithm has been used [4].

The paper is structured as follows: the well being method is recalled, the optimisation model is formulated and the proposed Genetic Algorithm to solve is illustrated. The results on a significant test system shows the goodness of the proposed method.

2. The Well-Being Model

The reliability criteria used in the well being model structure are either deterministic or probabilistic. The well-being analysis technique recognizes that the whole system operating states created by incorporating the system deterministic criteria can be categorized as being healthy, marginal or at risk. In this way, probabilistic concepts can be incorporated in a deterministic technique, thereby providing more information to system planners and operators about the system performance. This concept is illustrated in Fig. 1. In the healthy state all the equipment and security constraints are within limits while supplying the total system demand. In this state, there is sufficient reserve margin such as any single contingency can be tolerated without violating the limits. In the marginal state the operating constraints are within limits, but some specific single contingencies will result in being a limit being violated due to insufficient reserve margin. The operating constraints are violated in the risk state and the system may be required to shed load in this state. The total system states are so categorized into the three states, which can be expressed by Eq. (1) as follows:

$$P_h + P_m + P_r = 1 \qquad (1)$$

where P_h, P_m and P_r are the probabilities of the system being in the healthy, marginal and risk states, respectively.

The capacity of spinning reserve must be scheduled in such a way that the probability of system being in the risk state cannot be greater than a specified system risk that is determined by system operators.

$$P_r \leq SP_r \qquad (2)$$

where SP_r is system specified risk.

The spinning reserve is the rotating capacity in excess of the system load which is synchronized and immediately available to supply load. Non- synchronized or stand-by generation can be generally classified as rapid start and hot reserve units [1] [3].

Generating unit are committed for a specified time period during which additional generation can be made available after a time delay. The lead time required before a generating unit can be put into service depends on a number of factors including the type of unit in question.

Operating reserve assessment is historically done using deterministic approaches which do not assess the risk of the system and ignore the probabilistic or stochastic nature of system behaviour and component failure.

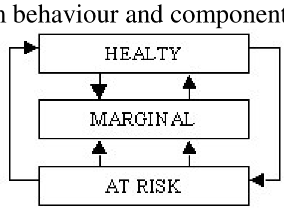


Figure 1 – System state in the well being model

In order to determine the probability that the system is in a successful or failed states a probabilistic model of generation unit are necessary. Starting from this knowledge the risk of the system to fall in so non healthy state is possible, building the risk curve as a function of generation and system reserves [1].

2.1 Generating Unit And Interruptible Load Models

Operating reserve can be generally divided into the two classes of unit reserve and system reserve. Unit reserve may be in the form of spinning or stand-by units. Figure 2 shows a modified two-state model [1] used in operating reserve assessment for spinning units. It is assumed that the system lead time is relatively short and therefore the probability of repair occurring during the small lead time is negligible. Under this condition the time dependent probabilities of the operating and failed states for a unit can be approximated by (3) and (4), respectively, at a given delay time of T.

$$P(failed) = \lambda T = ORR \qquad (3)$$

$$P(operating) = 1 - \lambda T \qquad (4)$$

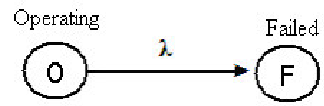


Figure 2 - Two-state model of a generating unit used in operating reserve evaluation.

Clearly, λ is the unit failure rate and ORR is the outage replacement rate [1]. The two-state model can further be modified by including postponable outages. In this case the total unit failure rate is reduced by the degree of postponability β. The probability of finding the unit in the failed state at a given time T in the future can be obtained using (5) [1].

$$P(failed) = (\lambda - \lambda\beta)T = (1-\beta)\lambda \quad 0 \leq \beta \leq 1 \qquad (5)$$

Rapid start and hot reserve units are represented by four and five state models as shown in Figs 3.a and 3.b respectively [1, 3]. The time dependent state probabilities are evaluated using a matrix multiplication technique [5].

$$\begin{vmatrix} P'_1(t) \\ P'_2(t) \\ P'_3(t) \\ P'_4(t) \end{vmatrix} = [A]^m \begin{vmatrix} P_1(t) \\ P_2(t) \\ P_3(t) \\ P_4(t) \end{vmatrix} \qquad \begin{vmatrix} P'_1(t) \\ P'_2(t) \\ P'_3(t) \\ P'_4(t) \\ P'_5(t) \end{vmatrix} = [A_1]^m \begin{vmatrix} P_1(t) \\ P_2(t) \\ P_3(t) \\ P_4(t) \\ P_5(t) \end{vmatrix} \qquad (6)$$

where

[P'(t)]= vector of state probabilities at time t,

[P(t)]= vector of initial probabilities,

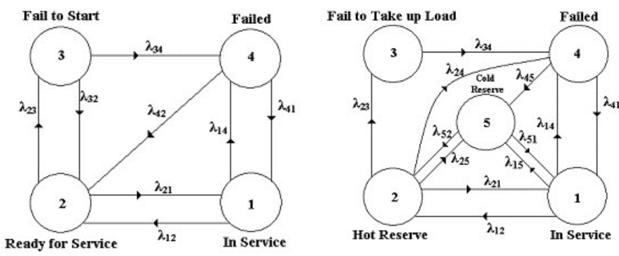
[A]= stochastic transitional probability matrix,

m= number of time steps used in the discretization process.

The vector of initial probabilities for the rapid start and hot reserve units are given in (7) and (8) respectively.

$$[P(t_r)] = [P_1(t_r) \quad 0 \quad 0 \quad P_4(t_r)] \qquad (7)$$

$$[P(t_h)] = [P_1(t_h) \quad 0 \quad 0 \quad P_4(t_h) \quad 0] \qquad (8)$$



(a) (b)

Figure 3 Four and five state models for rapid start and hot reserve units respectively.

where:

$$[P_4(t_r)] = \frac{\lambda_{23}}{\lambda_{21} + \lambda_{23}}\ ;\ P_1(t_r) = 1 - P_4(t_r) \qquad (9)$$

$$P_4(t_h) = \frac{\lambda_{23} + \lambda_{24}}{\lambda_{21} + \lambda_{23} + \lambda_{24}}\ ;\ P_1(t_h) = 1 - P_4(t_h) \qquad (10)$$

The probabilities of finding the rapid start and hot reserve units on outage given that a demand has occurred are given by (11) and (12) respectively. The unit availabilities are calculated using the complementary values of (11) and (12) [1].

$$P(down) = \frac{P_3(t) + P_4(t)}{P_1(t) + P_3(t) + P_4(t)} \qquad (11)$$

$$P(down) = \frac{P_3(t) + P_4(t) + P_5(t)}{P_1(t) + P_3(t) + P_4(t) + P_5(t)} \qquad (12)$$

Interruptible load can be modelled as an equivalent generating unit with zero failure rate or considered as a load variation as shown in Figs 4 and 5 respectively where τ is the load interruption time [1, 5].

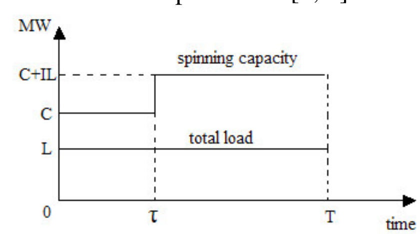


Figure 4 Equivalent unit approach model for interruptible load.

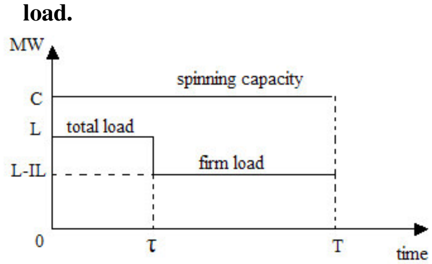


Figure 5 Load variation approach model for interruptible load.

2.2 Risk curve

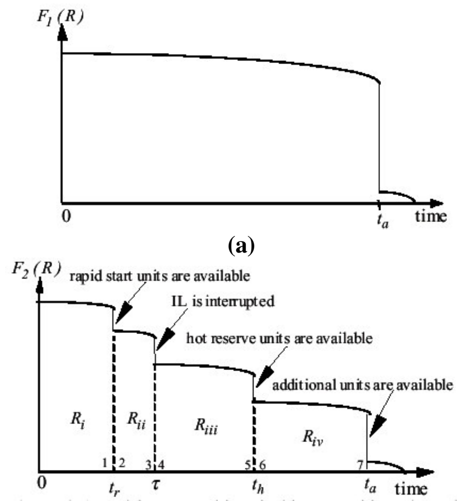
A unit commitment is necessary to assure an adequate level of generation reliability taking into account, firstly, probabilistic model of generation unit and then the load forecast uncertainty.

The unit commitment scheduling is started by committing a number of units starting with the most economic units. The initial number of committed units is therefore the minimum number of units required to satisfy (13).

$$\sum_{i=1}^{NO} G_i > L \qquad (13)$$

where NO is the number of on-line committed unit and G_i is the maximum capacity of unit i.

The Figure 6-a shows a possible area risk curve for a system with no stand-by units and interruptible load. This area risk curve represents the behavior of the system when only spinning and synchronized units (on-line units) are considered in the reserve calculations. A typical area risk curve for a system with rapid start, hot reserve units and interruptible load is shown in the Fig 6 b [1].



(b)

Figure 6 Load variation approach model for interruptible load.

The system risk can be calculated by simulating all possible contingencies. Evaluation can require a considerable computation time specially for systems with a large number of committed units. In order to decrease the computational time the partial system risk at each period is determined using a capacity outage probability table (COPT) [1, 6]. Using the initial number of committed units the system risk is calculated in the presence of rapid start units, interruptible load and hot reserve units.

$$P_r = R_i + R_{ii} + R_{iii} + R_{iv} \qquad (14)$$

where

$$R_i = \int_0^{tr} F_2(R)dt = P_{r1} - P_{r0}\ ;\ R_{ii} = \int_{tr}^{\tau} F_2(R)dt = P_{r3} - P_{r2}$$

$$R_{iii} = \int_{\tau}^{th} F_2(R)dt = P_{r5} - P_{r4}\ ;\ R_{iv} = \int_{th}^{ta} F_2(R)dt = P_{r7} - P_{r6}$$

The calculated system risk is compared with the specified risk as (2).

If (2) is not satisfied, an additional unit is added to the already on-line committed units and the above procedure is continued until the system risk is satisfied. In the

sequence, firstly rapid start unit are considered, then interruptible load and finally hot reserve unit. This is due to the different lead time of each kind of reserve.
Once the system risk is satisfied, the healthy and marginal state probabilities are calculated as follows.
The total decreasing risk due to the inclusion of stand-by unit and interruptible loads is calculated as (16) [1]:

$$TD_r = \int_0^{ta} F_1(R)dt - \int_0^{ta} F_2(R)dt \text{ ; } TD_r = P_{1r} - P_r \quad (16)$$

P_{1h} is determined from a COPT made of *NO* on-line committed units. The COPT represented in a descending order is shown in Table 1. The failed and operating state probabilities are calculated as follows [1, 6].

$$P(failed) \cong \lambda^i_{rsu} \times t_a \quad (17)$$

where

λ^i_{rsu} is the failure rate oh i[th] spinning unit

t_a is the lead time of additional generating unit in the sistem.

$$P(operating) \cong 1 - \lambda^i_{rsu} \times t_a \quad (18)$$

$$P_{1r} = \sum_{i=1}^{2^{NO}} P^i \times Q_i \quad (19)$$

$$Q_i = \begin{cases} 0 & if \quad L < C^i \\ 1 & if \quad L \geq C^i \end{cases} \quad (20)$$

Table 1 - COPT of the *NO* on-line spinning units.

Capacity in service	Individual probability
C^1	P^1
C^2	P^2
.	.
.	.
0	$P^{2^{NO}}$

The healthy state probability, P_{1h}, cannot be calculated using the COPT and is determined using a contingency enumeration technique. For a given contingency c it is assumed that m_1 set of units are in service and m_2 set of units are out of service.

$$m_1 + m_2 = NO \quad (21)$$

The probability of contingency c is calculated as (22).

$$P_c = \prod_{i=1}^{m1}\left(1 - \lambda^i_{sru} \times t_a\right)\prod_{j=1}^{m2}\left(\lambda^j_{sru} \times t_a\right) \quad (22)$$

$$\left(\sum_{i=1}^{m_1} G_i\right) - G_k > L \qquad k \in m_1 \quad set\ of\ units \quad (23)$$

$$P_{1h} = \left(\sum P_c \mid \text{if equation 23 is satisfied}\right) \quad (24)$$

$$P_{1m} = 1 - P_{1h} - P_{1r} \quad (25)$$

Comparing the two area risk curves $F_1(R)$ and $F_2(R)$

$$P_r = 1 - P_{1h} - P_{1m} - TD_r \quad (26)$$

$$P_r = 1 - P_{1h} - P_{1m} - TD_r + (P_{1h} + P_{1m})TD_r - (P_{1h} + P_{1m})TD_r \quad (27)$$

$$P_r = 1 - [P_{1h}(1 + TD_r) + P_{1r} \times TD_r] - [P_{1m}(1 + TD_r)] \quad (28)$$

$$P_r = 1 - P_h - P_m \quad (29)$$

$$P_h = P_{1h}(1 + TD_r) + P_{1r} \times TD_r \quad (30)$$

$$P_m = P_{1m}(1 + TD_r) \quad (31)$$

where P_{1h}, P_{1m}, P_{1r}, are the calculated healty, marginal and risk state probabilities considering only spinning capacity (area risk $F_1(R)$). P_h, P_m, P_r, are the actual healty, marginal and risk state probabilities using area risk curve $F_2(R)$.
Now load forecast uncertainty can be included in the well-being analysis as some deviation always exists between the forecast and the actual loads and so the probability that (13) would not be satisfied increase. The uncertainty is described by a normal distribution in which the distribution mean is the forecast load *L* and the standard deviation is obtained from previous forecasts. The normal distribution can be divided into class intervals as shown in Fig 7 whose number depends upon the accuracy required. The area of each class represents the probability of the load being at the class interval mid value. The operating state probabilities for each load level *k L* are first calculated and then weighted by the probability of the load being in each level [1, 6].

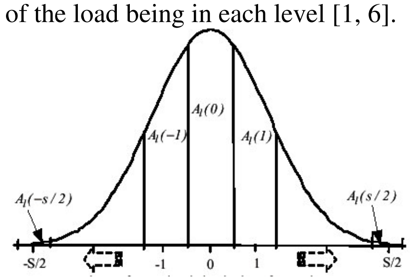


Figure 7 – Class of interval of normal distribution

3. Unit commitment problem via Genetic Algorithm

It can be noticed that the problem is a combinatorial one: to select the generation units and loads in the operating reserve to reach the fixed risk level. The iterative procedure do not assure the optimality of the unit commitment problem as it does not take into account available different reserve combination.
The main scope of the authors is to implement a procedure that find an optimal reserve among the different possible combination of generation reserve. The unit commitment problem is formulated with the goal of determining the mix and the number of on–line, spinning, stand-by unit, and the interruptible loads satisfying (2) at the minimum cost.
The unit commitment problem (UC) can be mathematically formulated as:

$$\sum_{i=1}^{k} c_i + \min \sum_{i=k+1}^{n} c_i x_i \quad (32)$$

s.v.

$$fr(x_1, \ldots, x_k, x_{k+1}, \ldots, x_n) \leq SP_r$$

$$x_1, \ldots, x_k = 1$$

$x_{k+1},\ldots,x_n = 0,1$

where

- k is the number of on-line committed units,
- n-k the number of supplemental reserve available
- c_i is the total production cost of unit i in the period considered,
- x_i is a binary variable which the status (on=1, off= 0) of unit i in the period considered
- f_r is the risk function, as recalled above, including on-line, spinning, rapid start, hot reserve units and interruptible loads.

The unit cost is determined by a following cost function [7]:

$$F_i = A_i + B_i \times P_i + C_i \times P_i^2$$

where:

F_i is operative costs of unit i

A_i, B_i, C_i are parametric costs of unit i

P_i is maximum capacity of unit i

From a mathematical viewpoint the above problem is a large-scale, mixed-integer, combinatorial, and non-linear programming problem. Unfortunately, exact solution techniques are not currently available for this type of problems. Among the most relevant approaches to generate solutions to the above problem in the paper genetic algorithm is used [4].

A genetic algorithm is a search technique based on the evolution of biological systems. The search starts with a set (population) of solutions (individuals) randomly generated and large enough. This set of solutions is the first generation.

The candidate solutions represent an encoding of the problem into a form that is analogous to the chromosomes of biological systems in particular it is a string of binary values. Each chromosome represents a possible solution for a given objective function. At each chromosome a fitness value, which determines its ability to survive and produce offspring, is associated

The UC solution is just a binary string of length “n”: the i-th element of the string is 1 if reserve associated to i-th unit is selected 0 otherwise. At each solution it is possible to relate a fitness value according to the objective function of UC.

As the objective function is a cost function and having in mind to maximize the fitness, the following fitness function for genetic algorithm purpose is chosen:

$$f(x) = C_{\max} - \left(\sum_{i=1}^{k} c_i + \sum_{i=k+1}^{n} c_i x_i \right)$$

where

$$C_{\max} = \sum_{i=1}^{n} c_i$$

C_{max} is the maximum value of objective function

UC is a constrained problem and the satisfaction of these constraints has to be taken into account.

The constrained minimization problem is refined as a minimization problem with no constraint inserting a following penalty function in the objective function. [4]

$$\Phi[fr(x)] = (fr(x) - SP_r)^2$$

So the problem formulation finally reduced in terms of fitness function as follows:

$$f(x) = \sum_{i=1}^{n} c_i - \left(\sum_{i=1}^{k} c_i + \sum_{i=k+1}^{n} c_i x_i \right) - r(fr(x) - SP_r)^2 \quad (33)$$

where r is an amplification coefficient and $fr(x)$ is the risk function.

GA now is able to solve the UC problem. Firstly, genetic algorithm determine the system risk considering only spinning and on line capacity unit. If (2) is satisfied, stop criterion is achieved, otherwise the genetic algorithm searches the stand- by, hot reserve units or interruptible loads to be added to this configuration.

The first generation is randomly generated from scratch. After the evaluation of the initial randomly-generated population the GA begins the creation of new generation of solutions.

Using uniform crossover and mutation procedures, with a probability of 0.02, new generations are obtained.

Two genotype are selected using tournament selection. Individuals are randomly splitted into various sets which size is arbitrary. The parents are the best individuals into each set. Selection pressure can be easily adjusted by changing the tournament size. If the tournament size is higher, weak individuals have a smaller chance to be selected.

Deterministic tournament selection selects the best individual in any tournament. The chosen individual can be removed from the population that the selection is made from if desired, otherwise individuals can be selected more than once for the next generation.

Tournament selection has several benefits, it is efficient to code, works on parallel architectures and allows the selection pressure to be easily adjusted.

Then, a new offspring genotype (new solution) is produced by means of: crossover and mutation.

The above procedure is repeated until a new generation are of solution is built, this replaces the parents. A elitism mechanism is used in the work: the best solution of every generation is copied to the next so that the possibility of its destruction through genetic operator is avoided.

4. Simulation results

The test system is constituted by five on-line and spinning, four rapid starts, three interruptible loads and three hot reserve units. Units main data are reported in table 1.

A total load of 7000 MW/h is considered and SP_r equal to 0.001 is valued as adequate for the system [6].

Considering only the on-line and spinning units, the system risk is 0,0046, that is higher than the limit previously assumed; other units have to be committed.

Two cases have been considered for two load configuration.

Table 2 - Generation Units data [7]

Rapid start units					Interruptible loads			hot reserve units		
N°	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Capacity	50	50	100	100	50	100	150	50	100	100
Cost	990	990	2103	2103	575	1151	1727	815	1650	1650

4.1 Case A

In a first instance, the load is considered deterministic. Choosing the units by classic method all the rapid start units have to be committed reaching a risk value of 0,0007 with a cost of €/h 6186,00. The proposed genetic algorithm is used to find optimal solution. The individual is a string of ten binary elements representing, in the order, the rapid start, interruptible loads and hot reserve respectively. A population of five elements is considered. All possible solutions are 2^{10}=1024. The algorithm stops after 100 generations. In fig 9 the best fitness over generations is depicted and in tab 3 the final population is reported. GA gives optimal solution at 45 generation i.e. generating only 125 possible solutions.
The solution suggested by the genetic algorithm (only interruptible loads) is cheaper than the classic one (€/h 1726,00) with a risk value blow the fixed limit: 0,0009.

Table 3 - Final population

#	Individual	Risk	Fitness
1	**0000110000**	**0.9999D-03**	**0.120280D+05**
2	0001100000	0.8263D-03	0.110760D+05
3	0001100001	0.7900D-03	0.942600D+04
4	1000101111	0.4922D-03	0.634700D+04
5	0001100110	0.5304D-03	0.861100D+04

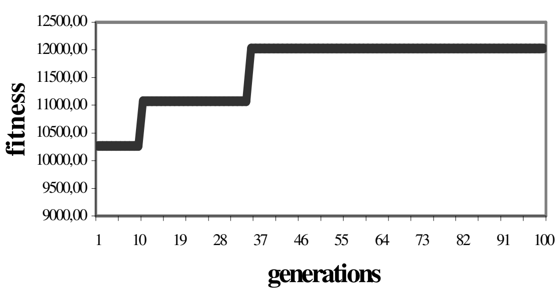


Figure 9 - Best fitness over generations

4.2 Case B

In this case a load uncertainty of 8% is taken into account. The system risk committing only the rapid starts units is higher than SPr, so two interruptible loads have to be committed reaching a risk value of 0.0009 with a cost of €/h 7912. The genetic algorithm in this case runs for 80 generations. In fig 10 the fitness of best individual over generation is depicted and in tab 4 the final population is reported. The genetic algorithm solution costs €/h 5556,00 with a risk level of 0.0008.

Table 4 - Final population

#	Individual	Risk	Fitness
1	**1000111111**	**0.1026D-02**	**0.503069D+04**
2	0101000100	0.2219D-02	-.361349D+06
3	1000001101	0.2225D-02	-.366478D+06
4	0001100100	0.2196D-02	-.347170D+06
5	1000110100	0.2226D-02	-.365482D+06

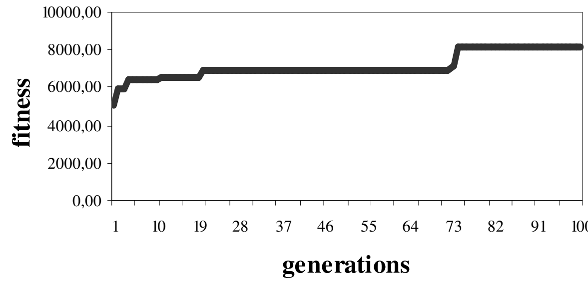


Fig. 10 Best fitness over generations

5. Conclusion

The paper concerns the unit commitment problem for operating reserve. The well-being approach is used to solve it. The resulting model to solve is a combinatorial problem that becomes hard to solve for real life power system. In the paper a genetic algorithm is used to solve in a efficient way this problem and to find the most economical solution. The numerical results obtained on a significant power system show the goodness of the proposed algorithm.

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