Analysis of Measurement & the Sensitivity for Multi State System Reliability With Genetic Algorithm Approach (GAA)

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Abstract

In this paper, I am described the measurement and sensitivity of Multi-state System (MSS) with genetic algorithms. In the field of reliability analysis, this paper's work is on the binary state system. I am considered that three measures are mostly used as MSS availability, MSS expected performance and MSS expected unsupplied demand. According to my concept, the MSS reliability is formulated and its structure function is defined for a coherent MSS, such as Boolean model are extended for the multi valued case, the stochastic process approach, Monto-Carlo simulation. In optimal allocation problems, I am finding the quality of a solution is the only information available during the search for the optimal solution. So, I have to use the heuristic algorithm for solving this problem and developing the family of genetic algorithms (GA) which is based on the simple principle of evolutionary search. This multi-objective genetic algorithm uses the universal moment generating function approach to evaluate the different reliability or availability indices of the system. The components are characterized by having different performance type, rate and reliability. In this paper, concept is presented describing GA developed for problems with multiple objectives. They differ primarily from traditional GA by using specialized fitness functions and introducing methods to promote solution diversity.

Key Words- Reliability, Availability, Genetic algorithms, Multi-objective optimization, Heuristic algorithm, Universal generating function (UGF).

1. Introduction

Every system element is performing its task with some different levels. As in power systems, generating limit has its nominal generating capacity, which is completely present if there are no failures. Few failure types can cause complete unit outage, whereas other types of failure can cause a unit to work with reduced capacity. If a system and its components have an arbitrary finite number of different states the system is formulated as a multi-state system. The physical feature of the performance is based on the physical nature of the system. So, it is important to measure performance rates of system components by their contribution into the entire MSS output performance. In few problems the performance measure is defined as productivity or capacity. Continuous materials or energy transmission systems, power Generation systems T. Aven [2], R. Billinton, R. Allan [9] are the example of MSS. Performance measure T. Back [4], R. Barlow, A. Wu [5] is considered as the speed of data processing. The main task of the system is to complete the task within the required time. B. Gnedenko, I. Ushakov [19] is also considered lot of types of MSS.

The MSS was devolved in 1970 J. Murchland [37], E. El-Neveihi, F. Proschan, J. Setharaman [17], R. Barlow, A. Wu [5], S. Ross [39]. In this paper, the basic concepts of MSS reliability are formulated, system structure function is assets for a coherent MSS. Definition and its types of coherence are defined by W. Griffith [21]. MSS reliability estimation is based on three different types T. Aven [3], such as Boolean models are extended for the multi-valued case; the stochastic process types and Monto carlo simulation. The structure function is useful for time consuming. A Monto carlo simulation model is mostly useful for reliability problem, but the

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main loss of the simulation technique is the time and expense involved in the development and execution of the model T. Aven [3]. In problems of MSS reliability analysis, if I applied the traditional techniques in optimization problem then system takes lot of time and it is so expenses. On it perverse, I used universal generating function (UGF) technique which is fast to be used in reliability problems. In this paper, the application of the UGF to MSS reliability analysis and optimization is considered.

I am choosing an optimization method which is easier, universal, chief and that's need the minimal requirement as to the knowledge for solving the problem of reliability optimization. Genetic algorithm is optimizing for optimization vectors as well as for combinatorial optimization. GA is applied on the redundancy allocation and structure optimization subject to reliability constraints D. Coit, A. Smith [15], M. Gen, R. Cheng R [18].

2. Measurement of Reliability in Multi-state System

The MSS is generalized with its measure in the space of states. Its characterization has to determine the MSS reliability indices. Indices can be evaluated as extensions of the corresponding reliability indices for a binary state system. T. Aven [3] and R. Brunelle, K. Kapur [12] also described his view on the MSS reliability measure.

Let us suppose, I am taking a system of n units and unit i having m_i states from failure functioning point to optimizing point. The system has different states M as determined by the states of its units. MSS state at time t is denoted as Z (t), where Z (t) □ {1, 2, 3, 4,….., M}. The performance rate R_m (output performance rate of MSS in at state m) is related with each state m □ {1, 2, 3, 4,…..M } and the system output performance distribution is defined by two finite vectors R and $n=\{n_m(t)\}=N_r\{R(t)=R_m\}$ (1 < m < M), where R(t) is random output performance rate of the MSS and $N_r\{e\}$ is a probability of event e.

I am determine a function F(R, T), where F(R, T) is function representing the desired relation between MSS performance rate R and demand T. if F(R, T) < 0, then condition is used as the criterion of an MSS failure. Mostly F(R, T) = R-T, which means that states with system performance rate less than the demand are interpreted as failure states.

MSS availability C(t) is the probability that the MSS will be in the states with performance level satisfying the condition F(R, T) ≥ 0. C is usually used for the steady state is called the stationery availability coefficient, or simply the MSS availability. MSS availability is the function off demand T. It is defined as:

$$C(T)=\sum_{F(R_m,T)\geq 0} n_m \qquad \text{...... (1)}$$

Where, n_m is the steady state probability of MSS state m. If $F(R_m, T) \geq 0$ then I am taking the resulting sum for state. The system operation period T is partitioned into "I" interval T_s $1 \leq s \leq S$ and each T_s has its demand level T_s.

The generalization of the availability G. Levitin, A. Lisnianski, H. Ben-Haim, D. Elmakis [23] is used as:

$$P_c(T,q)=\sum_{s=1}^{S} C(T_s)q_s \qquad \text{...... (2)}$$

Where T is the vector of possible demand levels T = {T_1, T_2,…..T_s} and q = {q_1, q_2,…..q_s} is the vector of steady state probabilities of demand level:

$$q_s = T_s \Big/ \sum_{s=1}^{S} T_s \qquad \text{...... (3)}$$

The value of MSS expected performance could be determined as:

$$D_R=\sum_{m=1}^{M} n_m R_m \qquad \text{...... (4)}$$

The unsupplied demand is proportional to penalty expenses, the expected unsupplied demand P_U may be used as measure of system output performance. If failure (F (R_m, T) < 0) the function – F (R_m, T) expresses the amount of unsupplied demand at state m, the P_U may be presented as:

$$P_U(T,q)=\sum_{s=1}^{S}\sum_{m=1}^{M} n_m q_s \max\ -F(R_m,T_s),0 \qquad \text{...... (5)}$$

I am considered MSS reliability assessment base on the MSS reliability indices introduced above. The reliability assessment methods presented are based on the UGF technique.

3. Reliability indices evaluation of MSS based on universal generating function

The UGF approach is based on definition of a u-function off discrete random variables and composition operators over u-function. The u function of a variable X is defined as a polynomial

$$u(z)=\sum_{m=1}^{M} n_m z^{X_m} \qquad \text{....... (6)}$$

Where the variable X has M possible values and n_m is the probability that X is equal to X_m. The compositions operators over u-function of different random variables are defined in order to the determined the probabilistic distribution for some functions of these variables.

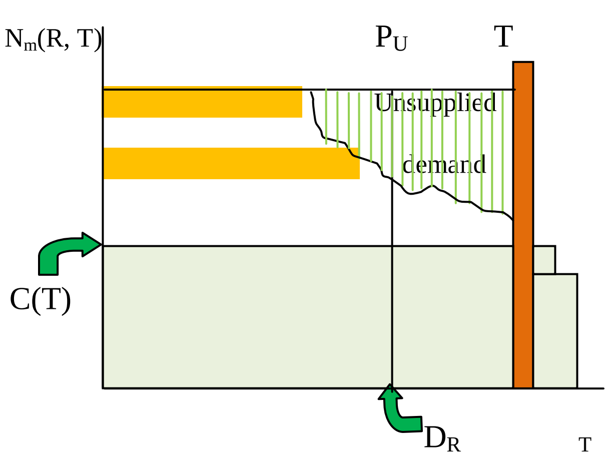

Fig.1: Indices for failure Criterion

UGF extend the widely known ordinary movement generating function B. Gnedenko, I. Ushakov [19]. The essential difference between the ordinary generating function and a UGF is that the latter allows one to evaluate an OPD for a wide range of systems characterized by different topology, different natures of elements and different physical nature of element's performance measures. UGF represented by polynomial U(z) can defined MSS OPD, it represent all the possible states of the system by relating the probabilities off each states n_m to performance R_m of the MSS in that state in the following form:

$$u(t,z)=\sum_{m=1}^{M} n_m(t) z^{R_m} \qquad \text{...... (7)}$$

In the steady state, the distribution of state probabilities is

$$n_m=\lim_{t\to\infty} N_r\ \ R\ \ t\ =R_m \qquad R(t)\in\ \ R_1,....R_M \qquad \text{...... (8)}$$

The MSS stationery availability may be defined according to equation 1, when the demand is constant or according to equation 2 in the case of variable demand. MSS OPD represented by polynomial U (z), the MSS availability can be calculated as

$$P_C(T,q)=\sum_{s=1}^{S} q_s \delta_C(U(z),F,T_S) \qquad \text{...... (9)}$$

The expected system output performance value during the operating time defined by equation 4 can be obtained for given U (z) using the δ_R operator:

$$P_R=\delta_R(U(z))=\delta_R(\sum_{m=1}^{M} n_m(t) z^{R_m})=\sum_{m=1}^{M} n_m R_m \qquad \text{...... (10)}$$

The expected unsupplied demand P_U for given U(Z) and variable demand according to equation 5. The using δ_U operator:

$$P_U(T,q)=\sum_{s=1}^{S} q_s \delta_U(U(z),F,T_S) \quad \text{.......} \ \textbf{(11)}$$

Firstly, I. Ushakov [40] introduced the UGF and formulated its principles of application. I. Ushakov [41]. The most systematically description of mathematical aspect of the method can be found in B. Gnedenko, I. Ushakov [19], where the method is referred to a generalized generating sequence approach.

Example: Discuss, If two Power system having the capacity of 200 MW at two different MSS. If due to some type of failure, the first generator reduced his capacity 80 MW and other type complete the outage. If due to some type of failure his capacity reduced 60 MW and other type reduced his capacity 30 MW in second generator and some type lead to complete the outage in second generator.

Solution: According to given condition, there are generate the three possible relative capacity level. It is generalized the performance by first generator-

$$R_1^{*}=0\ (Intialized\ stage)$$

$$R_2^{*}=\frac{80}{200}=0.4 \qquad R_3^{*}=\frac{200}{200}=1$$

According to second generator, there are generators the four possible relative capacity level-

$$R_1^{**}=0\ (Intialized\ stage) \qquad R_2^{**}=\frac{60}{200}=0.3$$

$$R_3^{**}=\frac{40}{200}=0.2 \qquad R_4^{**}=\frac{200}{200}=1$$

Now finding value of their corresponding steady-state probabilities for the first generator –

$$n_1^{*}=0.2\ (let) \qquad n_2^{*}=0.4 \qquad n_3^{*}=0.4$$

The second generator,

$$n_1^{**}=0.1\ (taking\, 10^{th}\ part\, of\ T)$$

$$n_2^{**}=0.10 \qquad n_3^{**}=0.4 \qquad n_4^{**}=0.4$$

Now evaluate the reliability indices for both MSS for T = 1 (given capacity level is 100MW)

a) The MSS u-function for the first and second generator, we know that

$$u(t,z)=\sum_{m=1}^{M} n_m(t) z^{R_m}$$

$$U_{MSS}^{*}\ z\ = n_1^{*} z^{R_1^{*}} + n_2^{*} z^{R_2^{*}} + n_3^{*} z^{R_3^{*}}$$

$$= 0.2 + 0.4z^{0.4} + 0.4z^{1}$$

$$U_{MSS}^{**}\ z\ = n_1^{**} z^{R_1^{**}} + n_2^{**} z^{R_2^{**}} + n_3^{**} z^{R_3^{**}} + n_4^{**} z^{R_4^{**}}$$

$$= 0.1 + 0.1z^{0.3} + 0.4z^{0.2} + 0.4z^{1}$$

b) The MSS stationary availability, by the formula-

$$n_m = \lim_{t\to\infty} N_r \ \ R\ t\ = R_m \qquad R(t)\in\ R_1,....R_M$$

$$P_C^{*}\ T\ = C^{*}(1)$$

$$= \sum_{R_m^{*}-T\geq 0} n_m = n_2^{*} + n_3^{*} = 0.4 + 0.4 = 0.8$$

$$P_C^{**}\ T\ = C^{**}(1)$$

$$= \sum_{R_m^{**}-T\geq 0} n_m = n_3^{**} + n_4^{**} = 0.4 + 0.4 = 0.8$$

c) The expected MSS performances, by the formula-

$$P_R = \delta_R(U(z)) = \delta_R\Big(\sum_{m=1}^{M} n_m(t) z^{R_m}\Big) = \sum_{m=1}^{M} n_m R_m$$

$$P_R^* = \sum_{m=1}^{3} n_m^* R_m^* = n_1^* R_1^* + n_2^* R_2^* + n_3^* R_3^*$$
$$= 0.2\times 0 + 0.4\times 0.4 + 0.4\times 1 = 0.56$$

It's mean 56%is the generating capacity for first generator.

$$P_R^{**} = \sum_{m=1}^{4} n_m^{**} R_m^{**} = n_1^{**} R_1^{**} + n_2^{**} R_2^{**} + n_3^{**} R_3^{**} + n_4^{**} R_4^{**}$$
$$= 0.1\times 0 + 0.1\times 0.3 + 0.4\times 0.2 + 0.4\times 1 = 0.51$$

It's mean 51%is the generating capacity for second generator.

d) The expected unsupplied demand, by the formula

$$P_U^* \ T \ = \sum_{R_m - T<0} n_m \ T - R_m$$

$$= n_1^* \ T - R_1^* \ = 0.2\times \ 1-0 \ = 0.2$$

$$P_U^{**} \ T \ = \sum_{R_m - T<0} n_m \ T - R_m$$

$$= n_1^{**} \ T - R_1^{**} \ + n_2^{**} \ T - R_2^{**}$$

$$= 0.1\times \ 1-0 \ + 0.15\times(1-0.3)$$

$$= 0.205 \approx 0.2$$

The absolute value of this unsupplied demand is 20MW for both generators. Multiply this index by considered system operating time, one can obtain the expected unsupplied energy.

Sensitivity Analysis and its importance

In this section, I am described the importance and sensitivity of MSS. Firstly I am finding the methods for evaluating the relative influence of component availability, which is useful information about the importance of these elements. Importance of evaluation is a main point in identifying bottlenecks in systems and in the identification of the most important components. It is a useful way to help the analyst find weakness in design and to suggest modifications for system.

Z. W. Birnbaum [10] was given the first theory of importance measure. It is shows the index characterizes the rate at which the system reliability changes with respect to changes in the reliability of a given element. Other measures of elements and minimal cut sets importance in coherent systems were developed by Barlow and Prosschan [7] and Vessely [42].

In multi-state systems the failure effect will be essentially different for system elements with different performance levels. So, when performance levels of system elements is estimated then it should be taken into safely mode. Some extensions of importance measures for coherent MSSs have been suggested, e.g. Barlow and Prosschan [7], W. Griffith [21], and for non-coherent MSSs A. Bossche [11].

The entire MSS reliability indices are complex functions of the demand *T*, which is an additional factor having a strong impact of an element's importance in multi-state systems. In a complex system structure, where each system component can have large number of possible performance levels and there can be a large number of demand levels *S*. I am demonstrating the method for the Birnbaum importance calculation, based on the UGF technique. The method provides the importance evaluation for complex MSS with different physical nature of performance and also takes into account the demand.

MSSs consisting of elements with total failure are the rate at which the MSS reliability index changes with respect to changes in the availability of a given element i. The element importance can be obtained for the constant demand W as:

$$\frac{\partial C(T)}{\partial c_i}$$

Where c_i is the availability of the i^{th} element at the given movement, C (T) is the availability of the entire MSS, which can be obtained for MSSs with a given structure, parameters, and demand.

Variables demand represented by

$$S_C(i) = \frac{\partial P_C(T,q)}{\partial a_i}$$

Where, T is vectors and q is the sensitivity of the generalized MSS availability P_C to the availability of the given element i. All the suggested measures off system performance (E_A, E_G, E_U) are linear functions of elements availability Therefore the corresponding sensitivities can easily be obtained by calculating the performance measures for two different values of availability. The sensitivity indices for each MSS element depend strongly on the elements place in the systems, its nominal performance level, and system demand.

Conclusions

This paper presented multi-objective GA by focusing on their components and its sensitivity when implementing multi-objective GA. Consideration of the computational realities along with the performance of the different methods is needed. Also, nearly all problems will require some customization of the GA approaches to properly handle the objectives, constraints, encodings and scale.

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