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Supervisory Evolutionary Optimization Strategy for Adaptive Maintenance Schedules

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***Abstract*—A supervisory strategy is proposed for improving the performance of an evolutionary-algorithm-based system-maintenance optimizer developed in our previous work for offshore power systems. The system-maintenance optimizer generates a set of initial maintenance plans, and exports them to an intelligent maintenance advisor connected to it for implementation. The proposed supervisory strategy uses a set of intelligent rules for adjusting the crossover and mutation rates of the present evolutionary algorithm. A mechanism is developed for refining and generalizing the supervisory rules according to the user's experience. The proposed supervisory strategy aims to improve the search ability and efficiency of the present evolutionary algorithm. Merits of the proposed supervisory strategy are demonstrated in case studies using our system-maintenance optimizer.**

***Index Terms*—Adaptive Maintenance Advisor, Offshore Power System, Supervisory Evolutionary Optimization Strategy, Supervisory Rules, System Maintenance Optimizer.**

I. Introduction

Condition-based maintenance is essential for extending component life in power and energy systems [1]. Evolutionary algorithms (EAs) or genetic algorithms (GAs) were applied to maintenance-related problems [2]–[9]. Unlike traditional maintenance optimization methodologies that only consider the equipment lifetime distribution [5]–[9], an adaptive condition-based maintenance scheme, which considers all the other operation-related variations, was proposed in our previous papers [10], [11]. This feature is particularly useful for offshore power systems because they are remotely located and difficult to access for data acquisition, inspection, and maintenance. Furthermore, the information collected during operations tends to be uncertain. There are two main parts in the proposed adaptive condition based maintenance scheme [10], [11], intelligent maintenance advisor and system maintenance optimizer. The intelligent maintenance advisor receives initial maintenance plans for all equipments from the system maintenance optimizer. It keeps track of the unplanned operational variations arising from ageing, weather, load factors, and uncertainties detected from key equipments, and reports the corresponding changes of load-point reliability and any excessive deterioration within the substation to the system maintenance optimizer [10], [11]. The optimizer can lead to the re-optimization of maintenance activities of all substations for balancing the reliability with costs of maintenance during operations. The system maintenance optimizer was developed by using a multi-objective evolutionary algorithm (MOEA) [10] for synthesizing the maintenance schedules of the system to provide the best tradeoff between its reliability and costs of maintenance.

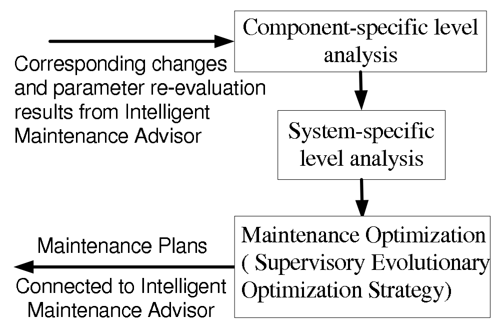

Fig. 1. System maintenance optimizer

Fig. 1 demonstrates the proposed system maintenance optimizer with three-blocks: component-specific level analysis, system-specific level analysis, and a multi-objective optimization block. In component-specific level analysis block, the Markov model generates reliability indices for individual components. In system-specific level analysis block, the system-configuration-related parameters and the load demand are used to generate the indices of the cost and availability at individual load points. The outputs of the system-specific level analysis block are used to calculate the two objectives (energy not served & overall cost) [12] to be evaluated by the multi-objective optimization block, which will guide the search towards optimal maintenance schedule.

In this paper, a supervisory evolutionary optimization strategy is proposed to improve the ability of the system maintenance optimizer. The proposed supervisory evolutionary strategy improves the performance of the EAs. Crossover and mutation rates of the EA are adjusted using a set of supervisory rules, making the system maintenance optimizer much more efficient.

This paper is divided into 5 sections. Section II describes the system maintenance optimizer. Section III discusses and analyzes existing improvements of EAs. Section IV describes the proposed supervisory evolutionary strategy, including supervisory rules, genetic operator designing and simplifying implementation of the supervisory evolutionary strategy. Section V presents the performance of the proposed supervisory evolutionary strategy. Section VI concludes the paper.

II. System Maintenance Optimizer

As shown in Fig. 1 [10], [11], the system maintenance optimizer includes three functional blocks: component-specific level analysis, system-specific level analysis, and multi-objective optimization module.

In component-specific level, multi-phase Markov model is employed to analyze the deterioration process of each component. In system-specific level, availability of cut sets is employed to obtain the system indices [12]. The proposed supervisory evolutionary strategy is used to implement the maintenance optimization module.

A. Component-Specific Level Analysis

The multi-phase Markov model for each component provides a quantitative connection between maintenance and reliability [12]. Discrete process phases are usually used and mostly based on regular Markov models [9]. The deterioration process of each component is modeled in finite states. If no maintenance actions are taken, the component at discrete time deteriorates following a Markovian manner. Transitions between states obey the transition matrix of the Markov chain.

Maintenance is able to extend component life, while component aging will shorten its life. The transition matrix P is updated at the beginning of each interval, incorporating the effects of maintenance as well as aging of the component. The deterioration level of the component at every interval can be inferred from past maintenance and deterioration record.

The mathematical relationship between transition probabilities and frequencies of the maintenance can be estimated by using the following [12]:

$$P^t(f_{m,t-1}, f_{M,t-1}) = \\ \sum_{i=1}^{N} P^t(f_{m,t-1}, f_{M,t-1}|P(S_{t-1}=i))P(S_{t-1}=i) \tag{1}$$

where $P^t(f_{m,t-1}, f_{M,t-1}|P(S_{t-1}=i)$ is the conditional transition probability matrix, influenced by the maintenance actions taken in interval $t-1$, the deterioration state of the component is in the state i; $P^t(f_{m,t-1}, f_{M,t-1})$ is the probability of being in the state i at the beginning of interval $t-1$.

In decision interval t, availability is used to measure the reliability of a component a. Availability A_a is the sum of the probabilities of all working states.

$$A_a = \sum_{i=1}^{N} P(S_t = i) \tag{2}$$

where $P(S_t = i)$ is the probability of being in the state i.

B. System-specific Level Analysis

In a substation, the failure of load point occurs in different combinations of failure events, known as cut sets. By definition, a minimum cut set is the smallest set of components whose failure can lead to the failure of the load point [13]. Minimum cut sets method is employed in our system maintenance optimizing [12]. The availability for a cut set consisting of two components can be evaluated by using the following equation for the parallel outage as:

$$A_{c_{ab}} = 1 - (1 - A_a)(1 - A_b) \tag{3}$$

where $A_{c_{ab}}$ is the availability of the cut set c, which consist of two components, a and b. Since each of these overlapping outages will cause system failure, all the overlapping outages are effectively in series from the reliability point of view. The system indices can therefore be evaluated by applying the methods for series components as the following:

$$A_{sys} = \sum_{s=1}^{n} A_s \tag{4}$$

where A_s is the availability of the s^{th} cut set, n is the number of the cut sets.

C. Multi-Objective Maintenance Optimization

Power systems are expected to provide good reliability, while operating as economically as possible with low operation cost and low failure cost. In our previous works [10], [12], the problem is formulated as a multi-objective search, aiming at finding a set of maintenance schedules which are comparatively 'equally good' for multiple objectives. The reliability objective is the approximated average un-served energy caused by the deterioration failure and chance failure. It can be calculated by the following equation:

$$f_{EUE} = (\sum_{t=1}^{T}\sum_{p=1}^{m}((1 - A_p) \times L_p))/T \tag{5}$$

where T is the number of decision interval; m is the number of load points in one substation; A_p is the availability at point p; L_p is the loss of load at load point p in one decision interval t [12].

The other objective is economic objective, f_{ecoO}, which includes the overall operation cost, f_{sysO}, and expected failure cost, f_{sysF}:

$$f_{ecoO} = f_{sysO} + f_{sysF} \tag{6}$$

$$f_{sysO} = \sum_{a=1}^{M} C_{o,a} + CapC \times Rate \tag{7}$$

$$f_{sysF} = \sum_{a=1}^{M} \{C_{f,a} \times \sum_{i=1}^{T} P_{i,f}\} \tag{8}$$

where M is the number of components in the system; $C_{o,a}$ is the operation cost of component a; $CapC$ is the capital cost in one substation; and $Rate$ is the interest and depression rate. The default value of $Rate$ is chosen as a constant, $Rate = 0.12$ [10], [12]. For component a, the operating cost $C_{o,a}$, which includes inspection cost and maintenance cost, is calculated by the following equation:

$$C_{o,a} = C_{in,a} \sum_{t=1}^{T} f_{in,t} + C_{mi,a} \sum_{t=1}^{T} f_{mi,t} + C_{ma,a} \sum_{t=1}^{T} f_{ma,t} \quad (9)$$

where $C_{in,a}$ is the inspection cost of component a; $f_{in,t}$ is the inspection frequency for component a in one decision interval t. $C_{mi,a}$ is minor maintenance cost for component a; $f_{mi,t}$ is the minor maintenance frequency for component a in one decision interval t. $C_{ma,a}$ is major maintenance cost for component a; $f_{ma,t}$ is the major maintenance frequency for component a in one decision interval t. The cost of economic objective will increase as the reliability improves, but the f_{EUE} is reduced at same time. Reliability can be improved at expense of the high cost with more frequency maintenance. In this study, all of the two contradictory objectives are functions of maintenance actions. Therefore, the multi-objective problem can be easily formulated as the following:

$$Minimize\ F_{obj} = Minimize\ \{f_{obj1}, f_{obj2}\} \quad (10)$$

where f_{obj1} and f_{obj2} are reliability objective and economic objective, respectively.

In our previous works, a system maintenance optimizer based on EAs had been designed to solve this problem [10], [12]. This paper improves the efficiency of the system maintenance optimizer by proposing a supervisory evolutionary optimization strategy.

III. Analysis of Existing Improvements of Evolutionary Algorithms

Due to their inherent parallelism, multi-objective evolutionary algorithms (MOEAs) are able to generate a set of optimal solutions in a single optimization run. Pareto-based MOEAs treat all the objectives equally in a search for the optima where none of the objectives can be further improved without degrading the others. More details about the Pareto optimality are given in [10], [12], [14], [15].

Genetic operators are key factors in improving the performance of many of such algorithms. Many improvement ideas have been proposed [16]–[24].

An EA, which keeps memory of every position that it had searched before, was reported in [16]. An archive was used to store all the solutions that had been explored before, and the EA was designed by using an adaptive mutation operator to void a revisit. Leonardo et al. [17] proposed an adaptive hybrid EA for technical loss reduction in distribution networks under variable demands and demonstrated the benefit of it by using case studies. Our previous works proposed an improved EA for quality of service (QoS) routing problems in optical fiber communication networks [18] and other previous work introduced supervised rules into the algorithm to propose a supervised EA for solving QoS routing problems [19]. However, it aimed at routing optimization problems, and supervised the algorithm procedure by using the routing information. This limits the application to other problems of the algorithm. Ye et al. [20] described some improvements on adaptive EAs and demonstrated the effectiveness of the improvements for reliability-relation applications. Jumping gene genetic algorithm (JGGA) was proposed and the simulation results demonstrated that JGGA was an effective scheme for some optimization problems [21], [22].

Among many techniques developed to improve the performance of EAs, the genetic operator adjusting methods are the most widely used approaches and the significance of p_c and p_m in controlling the performance of EAs had long been demonstrated by both empirical and theoretical studies [23], [24]. Typical values of p_c are in the interval [0.5, 1.0]. The higher the value of p_c, the quicker the new solutions are introduced into the population. The mutation p_m is another critical operator of EAs. Typical values of p_m are in the interval [0.001, 0.05] [24]. Large values of p_m will transform the EAs into a pure random search algorithm.

According to the adjusting methods, improved EAs can be classified into three categories: Mutation-first, Crossover-first, and Uncertain-order [20]. Mutation-first emphasizes on using higher mutation rates and lower crossover rates at beginning and lower mutation rates and higher crossover rates at the end.

Crossover-first approaches are opposite to the mutation-first approaches [20], [24]. Higher crossover rates are adapted at the beginning and higher mutation rates at the end. In [20], a new crossover-first approach and a new mutation-first approach in which the parameters were adjusted by using mean and variance of each generation were proposed in order to compare the two conflicting adaptive GA methods. The simulation result indicated that both of the two conflicting adaptive GA methods yielded better results than plain GA, and the new mutation-first GA was more efficient than the new crossover-first GA.

Except for Mutation-first and Crossover-first, other approaches are classified as uncertain-order schemes. Some of them adjust mutation or crossover rate in accordance with the fitness value, some of them varied mutation or crossover rate according to iterations of the algorithms.

It is established in all proposed strategies that large values of $p_c \in [0.5, 1.0]$, and small value of $p_m \in [0, 0.5]$ are ideal and essential for the success of algorithms [24]. Low value of p_c and high values of p_m will lead to the premature convergence of the algorithms.

IV. Proposed Supervisory Evolutionary Optimization Strategy

It is necessary that the designed genetic operator should have the ability to preserve the best solution of every population, and at the same time, it should be able to generate as many new models as possible to avoid getting trapped at local optimum.

This paper proposes a supervisory evolutionary strategy to improve the performance of EAs and the present system maintenance optimizer. The supervisory rules, which are refined and generalized from the experience of the improved EAs, are directly incorporated into the algorithms to supervise crossover and mutation steps of the algorithms to implement the system maintenance optimizer.

Three supervised rules are refined as follows:

(1) The supervisory rule about range of the genetic operators:

Mutation rate p_m and crossover rate p_c must satisfy $p_c \in [0.0, 1.0]$ and $p_m \in [0.0, 0.5]$.

(2) The supervisory rule about the relationship between fitness and genetic operators:

The individuals of the population with a higher fitness usually have a higher probability of producing good models. Therefore, they should have a lower mutation rate and a crossover rate to avoid destroying the good mode by high mutation rate or crossover rate. The individuals with low fitness usually have a lower probability of being good models, so these individuals should have lower mutation rate and crossover rate too. In order to explore the good models, the individuals with relatively mean fitness should have a higher mutation rate and a higher crossover rate since they may contain potential good models. After analyzing the supervisory rule of fitness, relationship between genetic operators and fitness are illustrated in Fig. 2.

(3) The supervisory rule about the relationship between generation and genetic operators:

In the early stage, in order to maintain the diversity of the individuals and prevent algorithms from prematurity. EAs need to generate as many new models as possible. In final stages, avoiding destroying good models and ensuring the converging of the algorithms are the most important.

According to the supervisory rule about generation, the genetic operators should be higher in the lower stage of evolution generation and lower in the higher stage of evolution generation. The trend of the curve in Fig. 3 shows the relationship between genetic operators and evolution generation. Both crossover rate and mutation rate decrease with the generation.

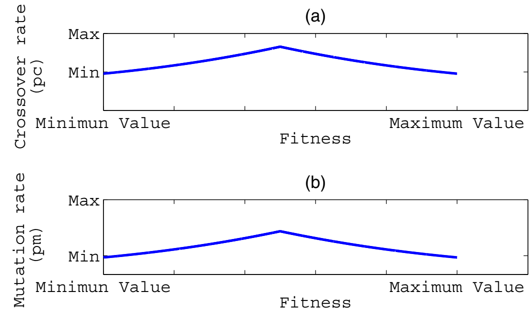

Fig. 2. Relationship between genetic operators and the fitness of the individuals

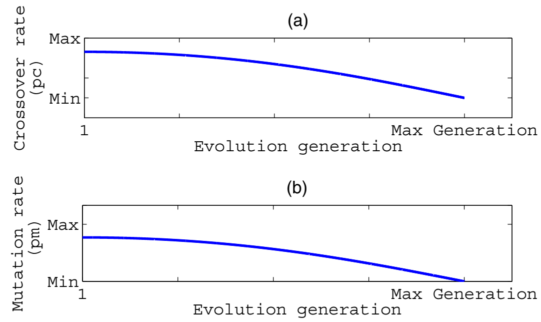

Fig. 3. Relationship between genetic operators and evolution generation of the algorithms

A. Implementation of the three supervisory rules

Crossover and mutation rates of the EA are adjusted according to the three above supervisory rules in connection with the process of the algorithms. Based on the first and second supervised rules, the following equation is designed by using the population size and the value of fitness as parameters.

$$x_1 = e^{-|pf*psize-1|} \tag{11}$$

where $psize$ is the value of the population size, pf is the percentage of an individual's fitness, which can be calculated by using the following equation.

$$pf(i) = \frac{fitness(i)}{\sum_{j=1}{}^{psize} fitness(j)} \tag{12}$$

where $fitness(i)$ is the obtained fitness value of i^{th} individual, $pf(i)$ is the percentage of i^{th} individual.

As shown in Eqn. 12, when the value of pf is near to $1/psize$, the fitness of the individual is near to the mean value of the fitness. The higher value of $|\ pf*psize-1\ |$, the lower value of x_1 will be obtained. x_1 satisfies $x_1 \in (0, 1]$ according to the above analysis.

According to the first and third supervisory rule, another equation is designed by using the current evolution generation as a parameter.

$$x_2 = \cos(\frac{(gen-1)}{Maxgen} \cdot \frac{\pi}{2}) \tag{13}$$

gen is the current evolution generation, $Maxgen$ is the maximum number of the evolution generation. The higher the number of evolution generation, the lower the value of x_2 will be obtained. x_2 satisfies $x_2 \in (0, 1]$ according to Eqn. 13.

We combine the two designed Eqns. 11 and 13, and the following equation is obtained.

$$\begin{aligned} x &= x_1 \cdot x_2 \\ &= \cos(\tfrac{(gen-1)}{Maxgen} \cdot \tfrac{\pi}{2}) \cdot e^{-|pf*psize-1|} \end{aligned} \tag{14}$$

The parameters of the designed Eqn. 14 include evolution generation, fitness of the individuals and population size of the EAs. The crossover and mutation rate are designed by using

Eqn. 14 as the following:

$$\begin{aligned} pc &= \frac{1}{1+e^{-x}} \\ &= \frac{1}{1+e^{-\cos(\frac{(gen-1)}{Maxgen}\cdot\frac{\pi}{2})\cdot e^{-|pf*psize-1|}}} \end{aligned} \quad (15)$$

$$\begin{aligned} pm &= \frac{1}{1+e^{-x}} - \varepsilon \\ &= \frac{1}{1+e^{-\cos(\frac{(gen-1)}{Maxgen}\cdot\frac{\pi}{2})\cdot e^{-|pf*psize-1|}}} - \varepsilon \end{aligned} \quad (16)$$

where ε is a adjusting parameter, which confirms pm to be an ideal mutation rate. In this paper, the value of ε is set to a constant $\varepsilon = 0.5$. According to Eqn. 15 and Eqn. 16, the designed crossover and mutation rates satisfy the following equation:

$$pm + pc <= 1 \quad (17)$$

Eqn. 15 and Eqn. 16 describe the relationship between evolution generation, individuals' fitness, and genetic operators. The above designed equations satisfy the three supervisory rules.

B. Simplifying Implementation of the Supervisory Evolutionary Strategy

It is important to reduce the computational time of EAs. Full inclusion of Eqns. 11, 12, 13, 14, 15 and 16 will add to computational resources. Their partial inclusion is proposed as follows without considering fitness for describing the relationship between evolution generation and genetic operators:

$$\begin{aligned} pc = & \frac{1}{1+e^{-x2}} \\ = & \frac{1}{1+e^{-\cos(\frac{(gen-1)}{Maxgen}\cdot\frac{\pi}{2})}} \end{aligned} \quad (18)$$

$$\begin{aligned} pm = & \frac{1}{1+e^{-x2}} - \varepsilon \\ = & \frac{1}{1+e^{-\cos(\frac{(gen-1)}{Maxgen}\cdot\frac{\pi}{2})}} - \varepsilon \end{aligned} \quad (19)$$

To further simplify the partial inclusion, the trend of the obtained curve from the proposed supervisory strategy can be simplified according to Fig. 3 by using simple linear function as the following:

$$pm = pm_o(1 - Gen/MaxGen) \quad (20)$$

$$pc = pc_o(1 - \frac{Gen}{MaxGen}) + pc_f \cdot \frac{Gen}{MaxGen} \quad (21)$$

where pm_o and pc_o are chosen maximum mutation rate and crossover rate of the algorithm. pc_f is the minimum crossover rate of the algorithm.

The trend of the curve in Fig. 3 can also be simplified by using a parabolic curve as the following:

$$pm = \quad pm_o(1 - Gen^2/MaxGen^2) \quad (22)$$

$$pc = pc_o(1 - \frac{Gen^2}{MaxGen^2}) + pc_f \cdot \frac{Gen^2}{MaxGen^2} \quad (23)$$

Other functions or equations may be designed to satisfy above three supervisory rules according to different applications.

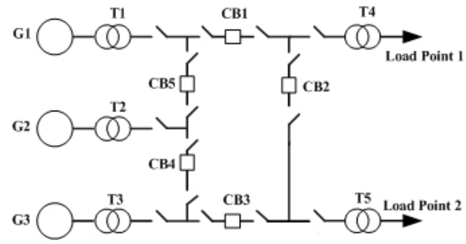

Fig. 4. Configuration of bus 07 in IEEE-RTS

V. Merits of the Proposed Supervisory Evolutionary Optimization Strategy

A. Parameter settings

All algorithms are coded in Matlab, and ran on a Pentium 4 PC, 3.16GHz, with 3.25 GB of RAM under Windows.

Fig. 4 shows the ring substation of Bus 07 in IEEE-RTS [1]. As Bus 07 is assumed to be the configuration of an offshore substation, the transformer and circuit breaker reliability are affected by planned as well as unplanned operational variations. Load-point reliabilities are affected by the transformers T1-T5 and circuit breakers B1-B5. Availabilities of transmission lines feeding the substations are assumed to be 100%.

Transformers and circuit breakers are modeled with three-deteriorated-state Markov chain model and system reliability model [12]. Initial parameters of the transformers and breakers ($p_{i,j}(i,j <= N)$) for Markov model and cost-related parameters (Capital cost ($CapC$), Maintenance cost ($C_{mi,a}$ and $C_{ma,a}$) and inspection cost ($C_{in,a}$)) are given in our previous paper [12].

NSGA II, a Pareto-based MOEA, as employed by us [12] is used in this paper for benchmarking. Crossover and mutation rate are set as $pc = 0.9$ and $pm = 0.05$ [12] for the benchmark MOEA. pc and pm are determined by Eqn. 18 to Eqn. 23 according to the corresponding supervisory rules for the proposed method.

B. Results and Discussion

Many experiments by using different parameters of population size and maximum generation are carried out to test the performance of the simplifying strategies of the proposed methods. The perfect Pareto fronts are obtained by both three simplifying strategies as well as the benchmark MOEA when population size is set at 200 and maximum iteration number is at 600. However, as shown in Table I, the proposed supervisory evolutionary optimizing strategy improves the performance of the algorithm by reducing the computational resources. Table I shows the performance of our proposed supervisory evolutionary optimizing strategy compared with the benchmark MOEA. At any pair of parameter settings, the proposed strategy requires less computational resources.

TABLE I
COMPARISON OF TIME CONSUMING BY USING DIFFERENT PARAMETER SETTINGS

Parameter Settings Population/Generation	Benchmark MOEA	Time Consuming (s) Using supervisory rule about Generation	Using linear simplified strategy	Using parabolic simplified strategy
100 / 100	181.945	131.884	93.804	119.871
100 / 200	361.094	260.569	186.647	241.776
100 / 600	1124.981	790.698	563.427	675.853
200 / 100	390.220	301.966	226.141	273.060
200 / 200	777.085	614.034	450.086	551.126
200 / 600	2441.058	1826.150	1416.674	1702.315

As shown in Table I, among the three simplifying strategies, the computational time of the linear-function simplification is the least, and almost half of the computational time has been saved from the original MOEA. The performances of the original algorithm are also improved by the other two simplifying strategies. In order to satisfy individual problem requirements, slightly different strategies for solving different problems are expected.

VI. CONCLUSION

This paper proposes a set of supervisory rules for our system maintenance optimizer. These rules adjust genetic operators and parameters for improving the convergence of EAs. For off line applications, a full set of supervisory rules can be used for adjusting the mutation and crossover rates according to all the variations of population, fitness and generation during convergence. For online applications, partial implementation of the supervisory rules is preferred for lesser computational time. Compared with the original MOEA, the present supervisory evolutionary strategy is more flexible, efficient and easy-to-implement.

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