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Hierarchical fuzzy logic system for implementing maintenance schedules of offshore power systems

C. S. CHANG

Zhaoxia WANG
Singapore Management University, zxwang@smu.edu.sg

Fan YANG

W. W. TAN

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Hierarchical Fuzzy Logic System for Implementing Maintenance Schedules of Offshore Power Systems

C. S. Chang, Zhaoxia Wang, Fan Yang, and W. W. Tan

***Abstract*—Smart grid provides the technology for modernizing electricity delivery systems by using distributed and computer-based remote sensing, control and automation, and two-way communications. Potential benefits of the technology are that the smart grid's central control will now be able to control and operate many remote power plant, optimize the overall asset utilization and operational efficiently. In this paper, we propose an innovative approach for the smart grid to handle uncertainties arising from condition monitoring and maintenance of power plant. The approach uses an adaptive maintenance advisor and a system-maintenance optimizer for designing/implementing optimized condition-based maintenance activities, and collectively handles operational variations occurring in each substation. The system-maintenance optimizer generates the initial maintenance plans for each substation with multiobjective optimization by considering only the design or average operational conditions. During operation, the substation will experience aging, control shifts, changing weather and load factors, and uncertain measurements. Residing on each host substation, the maintenance advisor will assess the adequacy of initial maintenance plans; and estimate the reliability changes caused by operational variations on the substation using a hierarchical fuzzy system. The advisor will also alert the maintenance optimizer on whether a reoptimization of its maintenance activities should be initiated for meeting the overall grid-reliability requirement. Three scenarios will be studied in this paper, which will demonstrate the ability of the proposed approach for handling operational variations occurring in an offshore substation with manageable computational complexity.**

***Index Terms*—Adaptive maintenance advisor, hierarchical fuzzy logic, multiobjective evolutionary algorithm, offshore substation, smart grid, system maintenance optimizer.**

I. Introduction

DEEP integration of condition-based maintenance within the smart grid is very desirable for extending component lifetime in power and energy system and achieving high operational efficiency in the overall power system [1]. Unlike traditional maintenance optimization methodologies that only consider the equipment lifetime distribution [2]–[6], an adaptive condition-based maintenance scheme is proposed in this paper. The key difference is that other operation-related variations are also considered. This feature is particularly useful for offshore power systems because they are remotely located and difficult to access for data acquisition, inspection, and maintenance. The information collected for smart-grid monitor/controller during operation contains fuzziness rather than crisp values. More powerful tools are hence needed to deal with these uncertainties for continuous monitoring.

Reliability analysis is performed regularly for condition-based maintenance [7]. Due to uncertainties arising inside and outside the equipment, it is often difficult to obtain exact reliability indices using conventional reliability analysis especially when conditions vary. Fuzzy sets theory was proposed by Zadeh [8] to resemble human reasoning under uncertainties by using approximate information to generate proper decision. Known as type-1 fuzzy logic, the methodology has been successfully used in many applications [9], [10] and for handling uncertainties related to component reliability [1] in power-system maintenance problems. Fuzzy Markov model has also been employed to describe transition rates [11].

The ability of type-1 fuzzy logic to model uncertainties is however restricted, as there is no fuzziness in type-1 memberships. Zadeh further proposed the type-2 fuzzy logic [12] and demonstrated its success over type-1 fuzzy sets for handling uncertainties in various fields [10], [12]–[14]. However, type-2 implementation for large-scale problems can be limited due to its heavy computational requirements.

Viewed as a variant of type-2 fuzzy sets, qualitative fuzzy sets [15] and blurred membership functions [16] were proposed by allowing a "small amount" of perturbations on each degree of membership functions. Membership perturbations were introduced in nonstationary fuzzy sets [17] for representing variations such as location, width, noise, etc., without changing the original inference process. Such perturbations may also be introduced in a hierarchical fuzzy system, which employs a set of high-level fuzzy rules for adjusting the settings of variables or input scaling factors of low-level rules as in a conventional fuzzy controller for tracking set-point changes and load disturbances [18]. We developed a similar approach by employing an independent set of fuzzy memberships to represent unplanned operational variations in offshore power systems for ensuring the quality of maintenance scheduling [19].

In this paper, we propose a hierarchical fuzzy system as one of smart control algorithms residing at each offshore substation. Our proposed fuzzy system has a flexible structure for easy integration with other control algorithms, and shares common objectives with them such as maximum energy delivery and minimum operational costs. Our proposed fuzzy system has also a variable structure, which engages low-level fuzzy memberships that represent ***planned*** operational variations occurring in each offshore substation; and high-level fuzzy memberships that map the ***unplanned*** operational variations as perturbations

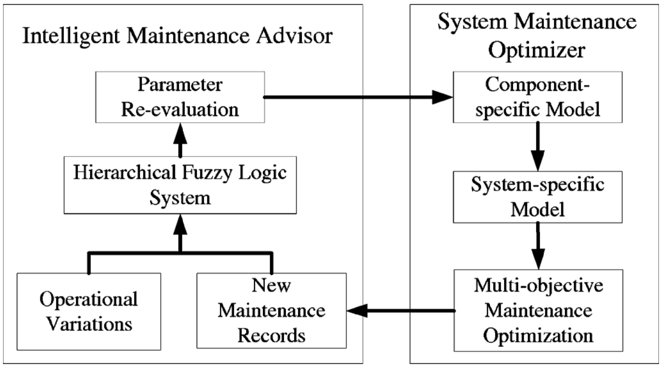


Fig. 1. Adaptive condition-based maintenance scheme.

in parameters defining each respective membership function of the low-level system. As shown in Fig. 1, our hierarchical fuzzy system links each offshore substation to its connected power grid, for alternately ***implementing*** and ***optimizing*** maintenance schedules of the offshore substation according to operational variations during operation.

The maintenance optimizer first assumes a set of best known or average operational conditions. The maintenance advisor receives and implements the initial maintenance plan for all its equipments from the system maintenance optimizer, and manages the hierarchical fuzzy system. The advisor keeps track of the unplanned operational variations arising from aging, weather, load factors, measurement and human-judgment uncertainties detected from key equipments. The initial optimal solutions will become suboptimal, leading to under- or over-maintenance during operation. The advisor reports the corresponding changes of load-point reliability and any excessive deterioration within the substation to the optimizer, which may lead to reoptimization of maintenance activities within the substation for balancing the reliabilities with costs of maintenance during operation.

The optimizer in Fig. 1 was developed by the authors using Pareto-based multiobjective evolutionary algorithm [19], [20] for synthesizing the maintenance schedules of a medium-sized power system (IEEE Reliability Test System [21]), by providing the best trade-off between its reliability and costs of maintenance.

This paper is organized into five sections. Section II describes the structure of our proposed hierarchical fuzzy logic system, the criteria for selecting planned and unplanned operational variations, the steps for handling these variations, the design of rules and assignment of computational tasks at the low and high levels. Section III describes three scenario studies for demonstrating the ability of our proposed hierarchical fuzzy system for handling operational variations occurring during operation with manageable computational complexity. Section IV and the Appendix conclude the paper.

II. Intelligent Maintenance Advisor With Hierarchical Fuzzy Expert System

A. Updating the Reliability Parameters for Each Component

Reliability indices, such as mean time to failure (MTTF) and failure probability (p_f), will not remain constant due to operational variations [19], [20], [22]. Changes of above reliability indices $\Delta\Lambda(t) = [\Delta\Lambda_{\mathrm{MTTF}}(t) \quad \Delta\Lambda_{p_f}(t)]$, which include MTTF $(\Delta\Lambda_{\mathrm{MTTF}}(t))$ and $p_f(\Delta\Lambda_{p_f}(t))$, are calculated for each component using the following fuzzy logic system:

$$\Delta\Lambda(t) = f_H(C(t)) \tag{1}$$

where $C(t)$ represents the set of operational variations of each component, and f_H represents the mapping function of the proposed fuzzy logic system from input to output. Having calculated $\Delta\Lambda(t)$, actual reliability indices of components are updated according to operational variations by

$$\mathrm{MTTF}(t) = \mathrm{MTTF}(t-1) + \Delta\Lambda_{\mathrm{MTTF}}(t) \tag{2}$$

$$p_f(t) = p_f(t-1) + \Delta\Lambda_{p_f}(t) \tag{3}$$

where MTTF$(t-1)$ and $p_f(t-1)$ are the original reliability indices obtained from the Markov model [19], [20], [22], [23], and MTTF(t) and $p_f(t)$ are the updated indices following the standard steps.

A hierarchical fuzzy logic system is proposed here for handling planned and unplanned operational variations of key components in each substation. Each operational variation as in $C(t)$ is connected with the others by fuzzy linguistic rules, which are derived from both the expert knowledge and mathematical strategies [10], [12], [19].

The rules of lower-level fuzzy system (RL) and high-level fuzzy system (RH) are illustrated by examples:

RL: if (age Variation is Younger) and (Load Factor is lighter) and (Operating Temperature Variation is same), then (Output is Much Worse (MW));

RH: if (Variation of Insulation Degradation is better), then (the impact is Left Shift (LS)).

Once the rules are established, the fuzzy logic system is used as a mapping function f_H from the input $C(t)$ to the output $\Delta\Lambda(t)$.

B. Overall Scheme of Hierarchical Fuzzy Logic System

The proposed fuzzy logic system has a computationally efficient two-level structure for each component (see Section III-B for case studies). The hierarchical fuzzy system in this paper is different from Mendel's type-2 fuzzy systems, as it is implemented by using type-1 inference mathematics rather than type-2 inference mathematics. Therefore, there is no comparison between the proposed hierarchical fuzzy system and type-2 fuzzy system. Compared with type-1 fuzzy system, the proposed hierarchical fuzzy system has the flexibility for accommodating new unplanned operational variations for any other equipment by simply adding a new set of memberships at the high level.

Inputs in the low level collect the amount of the planned operational variations occurring in each component. Fuzzy rules at this level then update the collective impacts of the planned operational variations on reliability indices on each respective component. The high level deals with the unplanned operational variations on each component in a similar manner. Several parallel fuzzy logic units in the high level are engaged with each using one unplanned operational variation as the input for evaluating its respective impact on the component's reliability. The low level also connects the planned and unplanned operational

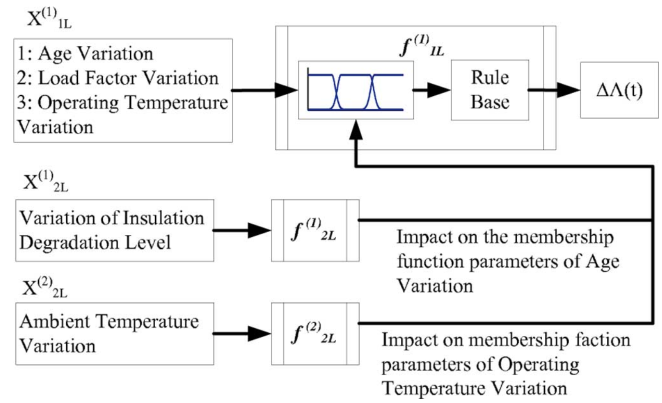


Fig. 2. Structure of hierarchical fuzzy logic system for each transformer.

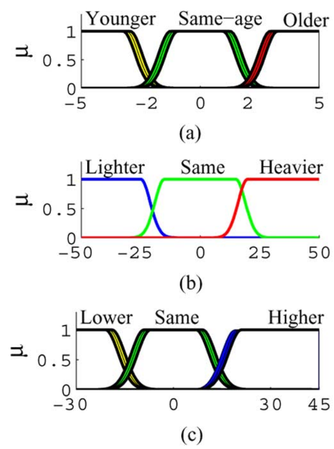


Fig. 3. Low-level membership functions for each transformer. (a) Input: age variation (yr). (b) Input: load factor variation (%). (c) Input: operating temperature variation (oC). (d) Output due to Figs. 3(a)–(c) and 5(c)–(d).

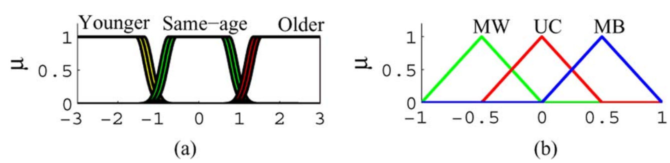


Fig. 4. Low-level membership functions for each circuit breaker. (a) Input: age variation (yr). (b) Output due to Figs. 4(a) and 6(b).

variations on each component for evaluating their overall impacts $\Delta\Lambda(t)$ on its reliability indices.

As a rule of thumb, input variables chosen in low-level memberships are widely used for modeling planned operational variations (Figs. 3 and 4). For example the operating temperature of a transformer is monitored closely for establishing its impact and mathematical model of the transformer's MTTF. In contrast, input variables chosen in the high-level memberships (Fig. 5), e.g., detected insulation degradation of the transformer or a transformer of similar type tend to occur in a more *ad hoc* manner, which is superimposed on the low-level memberships for computational flexibility as shown in Fig. 7 [16], [24]. Both the low- and high-level memberships must however be considered for their overall impacts on the transformer's MTTF.

Mathematically, all planned and unplanned operational variations are considered in parallel as follows:

$$\Delta\Lambda(t) = f_{1L}^{(1)}(X_{1L}^{(1)}, {f_{2L}}^{(1)}(X_{2L}^{(1)}), \ldots, {f_{2L}}^{(i)}(X_{2L}^{(i)}), \ldots, {f_{2L}}^{(n)}(X_{2L}^{(n)})) \quad (4)$$

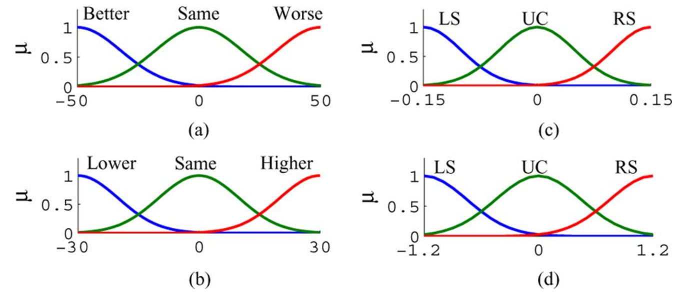


Fig. 5. High-level membership functions for each transformer. (a) Input: variation of insulation degradation level (%). (b) Input: ambient temperature variation ($^\circ$C). (c) Impact on functions in Fig. 3(a) due to variations in Fig. 5(a). (d) Impact on functions in Fig. 3(c) due to variations in Fig. 5(b).

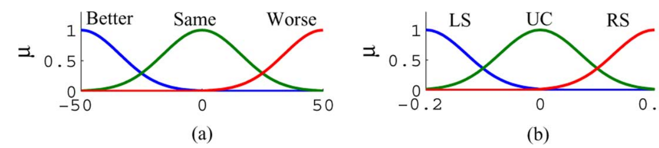


Fig. 6. High-level membership functions for each circuit breaker. (a) Input: variation of trip-coil defects level (%). (b) Impact on functions in Fig. 4(a) due to variations in Fig. 6(a).

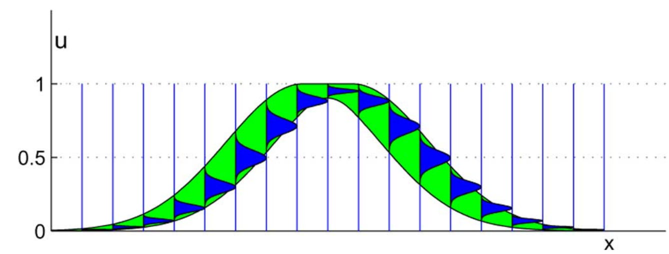


Fig. 7. A simple example of high-lever membership functions superimposed on low-level membership functions [16], [24].

where $X_{1L}^{(1)}$ represents the input of planned operational variations to the low-level fuzzy logic system, and $X_{2L}^{(i)}$ represents the input of unplanned operational variation to the ith high-level fuzzy logic unit. $f_{1L}^{(1)}$ and ${f_{2L}}^{(i)}$ are the mapping functions from inputs $X_{1L}^{(1)}$ and $X_{2L}^{(i)}$ to the output of the low-level fuzzy logic system and the ith high-level fuzzy logic unit respectively. n is the number of parallel fuzzy logic units in the high level, which is equal to the number of unplanned operational variations considered for each component.

Taking for example the transformer in our study offshore substation, $X_{1L}^{(1)}$ is an input vector representing variations of age, load, and operating temperature. Two high-level fuzzy logic units are used in parallel, within which $X_{2L}^{(1)}$ and $X_{2L}^{(2)}$ represent respectively variations of insulation degradation level [25] and ambient temperature of the transformer. As shown in Fig. 2, ${f_{2L}}^{(1)}(X_{2L}^{(1)})$ and ${f_{2L}}^{(2)}(X_{2L}^{(2)})$ give the corresponding impacts on reliability indices, which are considered together with the planned operational variations $X_{1L}^{(1)}$ (age and operating temperature) in the low level for calculating the overall impacts $\Delta\Lambda(t)$. For the circuit breaker, $X_{1L}^{(1)}$ denotes the age variation from the design age in the low level. Only one high-level fuzzy logic unit with $X_{2L}^{(1)}$ as the input is used for the circuit breaker for representing its defects level [26], which brings together the impact on the reliability indices with variation of age in the low level.

C. Fuzzy Representation of Planned and Unplanned Operational Variations and Fuzzy Inference Process

Reliability indices, such as mean time to failure (MTTF), will not remain constant due to operational variations. MTTF$(t-1)$ is the original reliability index obtained from the Markov model, and MTTF(t) is the updated index. The change of MTTF$(\Delta\Lambda_{\mathrm{MTTF}}(t))$ is the output of the fuzzy system to assess the impacts of operational variations on component reliability.

The universe of discourse of each input and its output is quantized in overlapping fuzzy sets as represented by their corresponding low- or high-level fuzzy membership functions:

i) Low-level fuzzy membership functions: aging, load, and operating temperature increases will worsen reliability. Fig. 3(a)–(c) shows these operational variations represented in various linguistic levels. Five output linguistic levels [MW, SW, UC, SB, MB] in Fig. 3(d) represent the change of MTTF of each transformer as in "Much Worse," "Slightly Worse," "Unchanged," "Slightly Better," and "Much Better." Similar to Figs. 3(a) and 4(a) shows the representation of age variations of circuit breaker. In Fig. 4(b), three low-level fuzzy logic variables [MW, UC, MB] are used to represent the change of MTTF for each circuit breaker. Each planned operational variation and the change of MTTF, are connected by the "IF-THEN" rules in the low-level fuzzy logic system. For example, in Fig. 3(a)–(d), if inputs are [a) (the age variation is "older") and b) (the load factor variation is "heavier"), and c) (the operating temperature variation is "higher")], then the output is [d) (the change of MTTF for this transformer will be "MW")].

ii) High-level fuzzy membership functions: unplanned operational variations selected for the high level are dynamic and time-varying on a daily or even an hourly basis. The set of unplanned operational variations selected in this work is: for each transformer its insulation degradation and ambient temperature variation, and for each circuit breaker its defects such as those occurring in trip coils. Degradation in transformer insulation can be detected with dissolved gas analysis [25] with transformer-oil samples to be collected regularly. The universe of discourse of insulation degradation is quantized into [better, same, worse] as in Fig. 5(a); whereas variations of ambient temperature are quantized into [lower, same, higher] as shown in Fig. 5(b). The trip-coil defects in circuit breakers can be detected by current signature [26], which are quantized in [better, same, worse] as in Fig. 6(a).

iii) Connecting low- and high-level fuzzy memberships: each unplanned operational variation brings about an impact on reliability indices by influencing respective planned operational variation in the low level, as illustrated in Fig. 2. Taking for example Figs. 5(a) and 3(a) as well as Figs. 5(b) and 3(c), the degradation of transformer insulation will speed up transformer aging; whereas the change of ambient temperature will have an impact on each transformer's operating temperature. The influence on each respective low-level input can be achieved by shifting its corresponding membership along the universe of discourse. The resultant shifting is quantized into [LS, UC, RS] to represent "Left Shift," "Unchanged," and "Right Shift," as in Figs. 5(c) and (d) and 6(b). Each unplanned operational variation and the consequent shifting are connected by the "IF-THEN" rules in each high-level fuzzy logic unit. For example, in Fig. 5(a) and (c), if the input is [a) (the variation of insulation degradation level is "worse")], then the output is [c) (the shifting of membership function for the age variation (represented in Fig. 3(a)) will be "LS"]. The resultant shifting of the low-level membership functions is represented by the shaded area in Figs. 3(a) and (c) and 4(a).

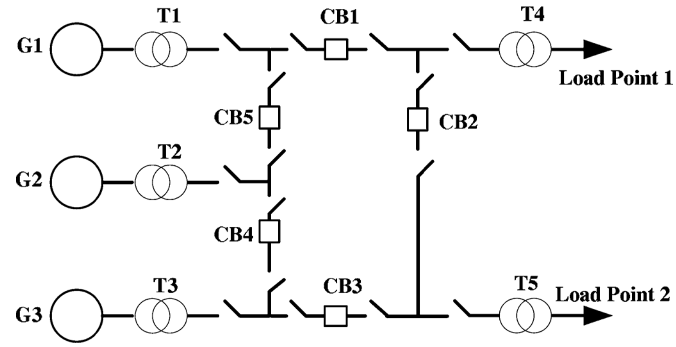


Fig. 8. Configuration of bus 07 in IEEE-RTS.

III. Results and Discussions

A. Description of Offshore Substation Used in Case Studies

Fig. 8 shows the ring substation of Bus 07 in IEEE-RTS [21], whose load-point reliabilities are affected by the transformers T1–T5 and circuit breakers CB1–CB5. Reliabilities of generators G1–G3 are assumed constant, whose variations with operational conditions are being investigated. As Bus 07 is assumed to be an offshore substation, the transformer and circuit breaker reliability are affected by planned as well as unplanned operational variations. The study period is set for 20 years.

The two load points in Fig. 8 are assigned different priorities with load point 2 having a higher priority because it transfers most of the output from generators G1–G3 to the connected grid. Load point 1 has a lower priority because it provides a smaller part of the output from generators G1–G3 to local consumers. Case studies are focused upon power exports from the offshore power system, which can be reversed by simply changing the data. The population size for Non-dominated Sorting Genetic Algorithm-II (NSGA II) [20], [27] is set at 80, the number of generations is 90, and the crossover and mutation rates are set at 0.8 and 0.05 respectively. The maintenance cost data is listed in [20]. A review of the NSGA II developed for this work is given in the Appendix.

B. Specification of the Base Case and the Three Scenario-Study Cases

Three scenario-study cases are specified as below for showing the application of our proposed approach. These scenarios are each reoptimized during operation using the steps

TABLE I
AVERAGE OPERATIONAL CONDITIONS FOR BASE CASE OPTIMIZATION

	Components	
Condition	Transformer	Circuit breaker
Age (Yr)	Increase from 1 (beginning of study period) to 20 (end of study period)	Increase from 1 (beginning of study period) to 20 (end of study period)
Load factor	50	–
Average operating temperature(^oC)	30	–

of Fig. 1 to reestablish the optimal maintenance schedules for meeting the new operational variations. For comparison, a base-case study is also carried out (Table I).

Specification of the Base Case with maintenance plans previously optimized using the steps as shown in Fig. 1 with assumed average operational conditions (Table I). We also assume a linear aging process and the same age for all components from the beginning of the maintenance period. Other planned operational conditions (load and operating temperature) are assumed constant throughout the maintenance period. No unplanned operational conditions are considered. In other word, the unplanned operational variations are assumed to be zero.

Specification of the Three Scenario-study Cases: During operation, all components will experience different aging and/or different operational variations. To demonstrate this, three scenario study cases are listed below:

Scenario 1: Worse-than-anticipated aging and deteriorations where each transformer and each circuit breaker in Fig. 8 are suffering from worse aging than the base case from the beginning of the study period. These elements will also experience a new set of insulation degradation and trip-coil defects as shown in Fig. 9. Consequently, the base-case maintenance activities will not be able to meet the required reliability leading to higher energy-not-served and failure cost. Therefore, maintenance activities will need to be reoptimized according to the excessive aging and deteriorations for providing higher reliability.

Scenario 2: Lower-than-anticipated transformer loading where reliability indices of the respective transformers have to be reestimated according to the new loads (Fig. 10), which will necessitate reoptimization and scale-down of maintenance activities.

Scenario 3: Worst-than-anticipated working environment & ambient temperature where transformer reliabilities are deteriorating excessively as in Fig. 11, which will necessitate reoptimization and scale-up of maintenance activities. This is similar but not exactly the same as Scenario 1, where our methodology will deal with them differently.

The remaining section will show how the proposed hierarchical fuzzy logic system is effective for reestablishing the optimal maintenance schedules for the four above study cases. We assume the same operational conditions for all the components of each same type in each scenario.

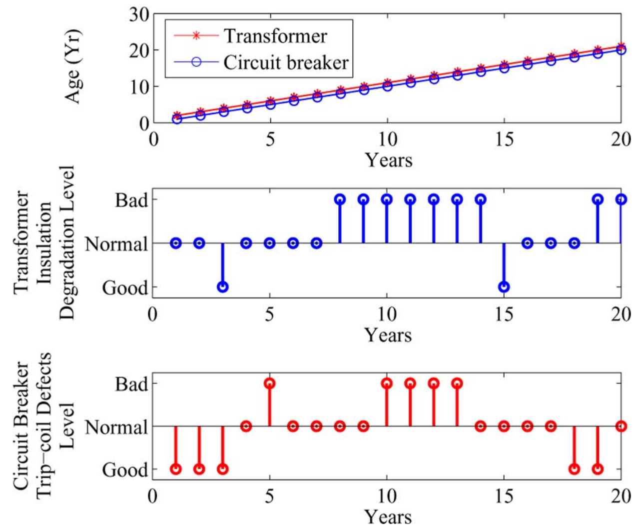


Fig. 9. Worse-than-anticipated aging and deteriorations.

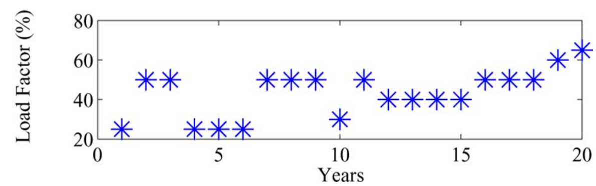


Fig. 10. Lower-than-anticipated transformer load factor.

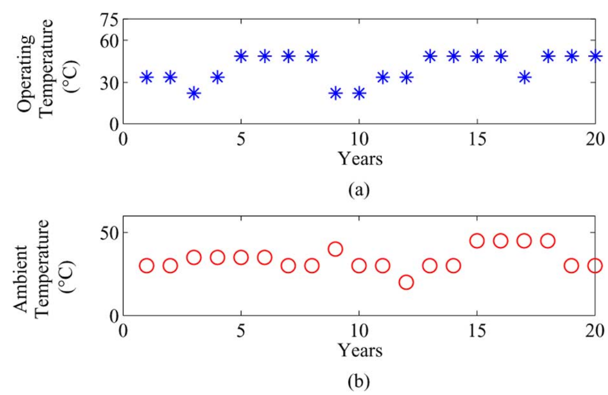
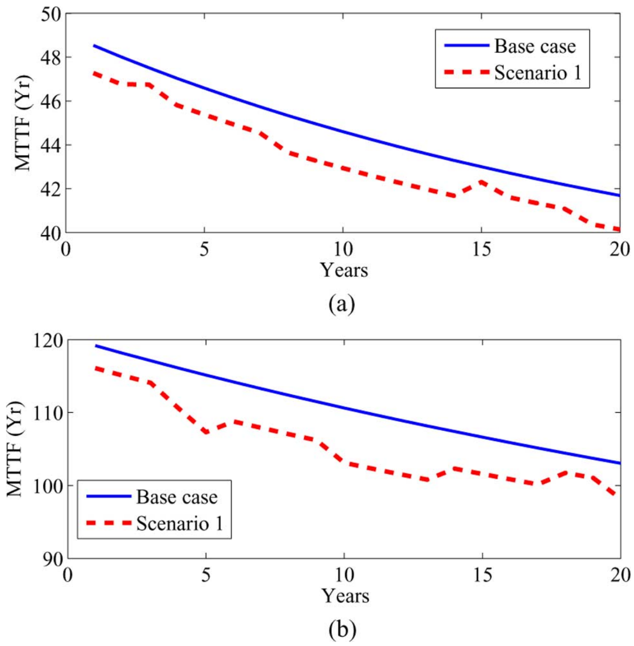


Fig. 11. Worst-than-anticipated working environment and ambient temperature.

C. *Study Results—Impacts of Unplanned Operational Variations on Optimal Maintenance Schedules*

Scenario 1 Result: Worse-than-anticipated aging and deteriorations Age variations of each transformer and circuit breaker are represented by the low-level membership function as in Figs. 3(a) and 4(a). Variations of insulation degradation level of each transformer and the trip-coil defects level of each circuit breaker are assessed as shown in Fig. 9 and each represented by the high-level membership functions in Figs. 5(a) and 6(a).

Fig. 12(a) and (b) shows the variation of MTTF of the transformer (T1) and circuit breaker (CB1) by implementing the base-case maintenance plan. Comparing with the base case, it is seen that due to excessive aging and deteriorations, the MTTF's of each transformer and circuit breaker are lower than those under Scenario 1. The overall energy not served (ENS) in Scenario 1 is also more than the base case as shown in Fig. 13.



(a)

(b)

Fig. 12. Variations of MTTF after implementing base-case maintenance plan. (a) Transformer. (b) Circuit breaker.

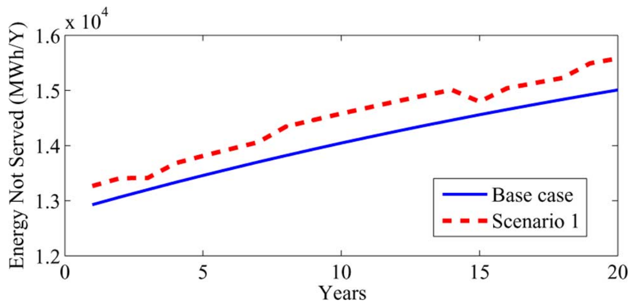
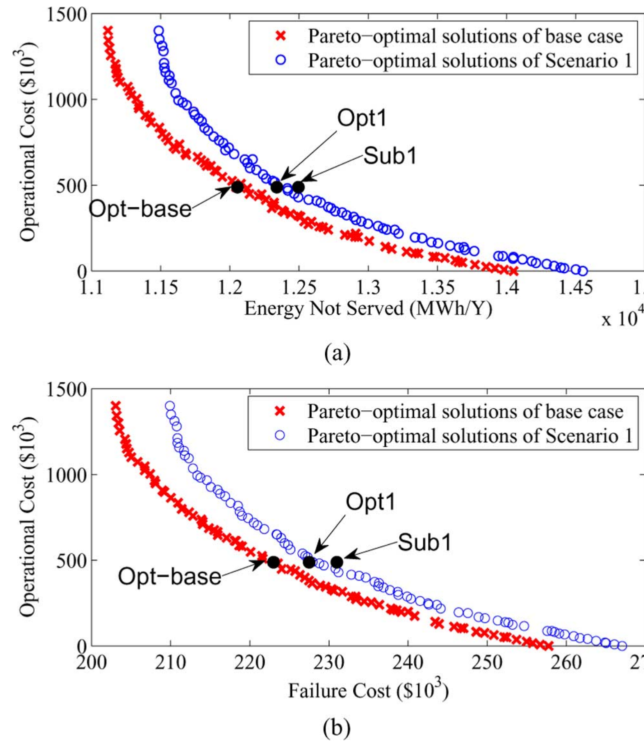


Fig. 13. Variation of energy not served after implementing base-case maintenance plan.

We choose ENS instead of the loss of load probability (LOLP) because some systems having close LOLP can have much different ENS and a system having lower LOLP can have higher ENS than the others with higher LOLP [20], [22]. FLOLP is a fuzzy description of the probability of load exceeding an available capacity [1], which was found by us having the same problems as with LOLP.

The Pareto front in Fig. 14 shows that the proposed fuzzy expert system helps to reestablish optimal maintenance schedules and maintain the schedules "Opt1" on the pareto-optimal front. As shown in Fig. 14, one solution on the Pareto-optimal front for the base case, Opt-base, is chosen as the best solution with ENS of 1.204×10^4 MWh/y, failure cost of $\$242.231 \times 10^5$, and operational cost of $\$244.890 \times 10^5$. However, Opt-base will no longer be optimal for Scenario 1 due to new operating conditions. Implementing Opt-base to Scenario 1 will result in higher ENS of 1.247×10^4 MWh/y and higher failure cost of $\$242.314 \times 10^5$, as denoted by Sub1 in Fig. 14(a) and (b). Therefore, a new Pareto-optimal front is obtained by reoptimizing the maintenance schedules. A new optimal schedule Opt1 is obtained as a result of the collaborative effort of the maintenance optimizer and the maintenance advisor (Fig. 1), providing a higher reliability than Sub1 with the same operational cost.



(a)

(b)

Fig. 14. Pareto fronts of base-case and scenario-1 studies. (a) Operational cost vs. energy not served. (b) Operational cost vs. failure cost.

The maintenance gains and costs of Sub1 and Opt1 are listed in Table II.

Scenario 2 Result: Lower-than-anticipated transformer loading The load factor variation of each transformer is represented by the low-level membership functions in Fig. 3(b). In this scenario, maintenance activities will become excessive if the base-case schedules are implemented directly. Sub2 and Opt2 in Table II show the reliability gains and costs of directly implementing Opt-base to this scenario and reoptimizing the schedules, respectively. Comparing Sub2 with Opt2, it is seen that Opt2 provides lower ENS and failure cost than Sub2 with the same operational cost. The result here demonstrates the necessity of reestablishing optimal schedules for this scenario.

Scenario 3 Result: Higher-than-anticipated temperature The operating temperature and ambient temperature of each transformer are each represented by the low- and high-level membership functions in Figs. 3(c) and 5(b). Our proposed hierarchical fuzzy logic indicates correctly that higher-than-anticipated operating temperature and ambient temperature degrade reliability. As a result, it is necessary to reestablish maintenance schedules. Sub3 in Table II shows the reliability and costs from directly implementing Opt-base to this scenario, and Opt3 is one reestablished solution. It is obvious that Sub3 is not optimal because it causes worse reliability with the same operational cost than Opt3.

In contrast to onshore power systems, offshore power systems are often remotely located, and are therefore more exposed to unplanned uncertainties especially during adverse weather conditions. This paper proposes a hierarchical fuzzy system which overcomes the limitation of conventional fuzzy systems in coping with such uncertainties. The conventional and the proposed hierarchical fuzzy system are compared in Table III,

TABLE II
RELIABILITY GAINS AND MAINTENANCE COSTS

Study scenarios	Maintenance scenarios	Operational cost ($\$ \times 10^5$)	Energy not served (ENS) ($MWh/Y \times 10^4$)	Failure cost ($\$ \times 10^5$)
Base case	Opt-base	4.890	1.204	2.231
Scenario 1	Sub1	4.890	1.247	2.314
	Opt1	4.890	1.234	2.279
Scenario 2	Sub2	4.890	1.196	2.229
	Opt2	4.890	1.180	2.201
Scenario 3	Sub3	4.890	1.261	2.346
	Opt3	4.890	1.250	2.324

TABLE III
RELATIVE CAPABILITY FOR COPING WITH PLANNED AND UNPLANNED UNCERTAINTIES BETWEEN THE CONVENTIONAL AND THE PROPOSED HIERARCHICAL FUZZY SYSTEMS

	Conventional fuzzy systems	Proposed hierarchical fuzzy system
Planned operational variations	Yes	Yes (using low-level memberships)
Unplanned operational variations	No, unless with excessive number of inputs and fuzzy rules (see earlier discussion)	Yes (using high-level memberships)

which favors our proposed system for coping more effectively and efficiently with unplanned uncertainties.

IV. CONCLUSION

This paper proposes a modular and flexible architecture for updating the change of load-point reliability resulting from unplanned operational variations during operation of a system optimized maintenance plan. As an essential component of smart grid, the proposed maintenance advisor will report any excessive deterioration of load-point reliability within each substation, and require the maintenance optimizer to dynamically reestablish the substation's optimal maintenance activities for meeting the desired reliability with lowest cost during operation.

Operational variations arise continually due to unplanned or unforeseen weather changes and condition-degradation of transformers and circuit breakers, which are shown in this paper to have significant impacts on the maintenance scheduling of offshore substations. Our hierarchical fuzzy logic is demonstrated to be computationally efficient and flexible for handling these unplanned operational variations in a medium sized power system, which should therefore have a good potential for large-system applications.

One main contribution of this paper is on development of an online platform residing on each offshore substation for providing users with a library of automatic, robust, flexible, modular, expandable, and intelligent algorithms for optimizing and implementing condition-based maintenance on offshore power systems, while responding promptly and efficiently to unpredictable operational and weather variations frequently encountered during offshore operations. Due to its flexible structure, our platform should integrate well with other control algorithms of grid management system at each substation, which are designed with the common objectives of maximum energy delivery as well as maximum operational efficiency.

APPENDIX
MAINTENANCE OPTIMIZER

The task of system maintenance optimizer is to optimize the maintenance schedules for an offshore substation and its connected grid for providing the best trade-off between multiobjective functions such as its reliability and costs of maintenance.

Having the main advantage of computing the entire Pareto Front in one single rather than many algorithm runs, evolutionary algorithms have been widely used for solving multiobjective optimization. Their other advantage is simplicity in terms of formulation and implementation for solving problems especially with noncontinuous objective functions in a large-scale search space. Comparing with many conventional optimization approaches, evolutionary algorithms do not require any gradient information of their objective and other functions during computation. Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is one of standard approaches of evolutionary algorithms, which have been reported by the authors [20], [28] and other researchers [27] to attain better spread of solutions and convergence near the final Pareto front with favorable comparisons over many other well-known algorithms. The authors have also developed and investigated several variants of the NSGA II, e.g., NSGA DE (Differential Evolution) for demonstrating the robustness of the nondominated sorting methodology [28].

As shown in Fig. 1, the system maintenance optimizer includes three functional blocks: component-specific model, system-specific model, and multiobjective maintenance optimization.

A. Markov Model for Each Component

Similar to [20], the underlying deterioration of each component during maintenance is modeled in 4 states. S_i, $i = 1$, 2, 3, 4. S_1 denotes the "as good as new" state, S_2 and S_3 are the states with different levels of deteriorations, and S4 represents the failed state. Transitions between states obey the transition matrix of the Markov process. Normally, maintenance is estimated to speed up the restoration rates and thereby extend component lifetime. The reliability indices, mean time to failure (MTTF) and failure probability (p_f) of each component, can be calculated easily following the standard steps for the Markov model [20], [22], [23], [28].

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 $i (i = 1, 2, \ldots, N)$:

$$A_a = \sum_{i=1}^{N} P(S_t = i) \tag{5}$$

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

B. System-Specific Model for Overall System

The configuration of a power system directly affects the load-point reliability. Minimum cut-sets method is used in this study to analyze the impacts of complex configuration on system reliability in terms of energy not served (ENS).

For a substation with more than one load point, different priorities will be assigned to each load point in order to ensure the load can be first transferred to the more important load point. After satisfying the load demand of higher priority, the extra load will then be transferred to the other load points. Interested readers are encouraged to refer to our work [20], [22], and [23] for more details.

C. Multiobjective Maintenance Optimization

The operational cost of overall substation usually increases as the reliability is improved, but the energy not served (ENS) and failure cost can be reduced. Similar to our early work [20], maintenance actions (no maintenance, minor maintenance, and major maintenance) in each interval are adopted as the variables of the three objectives functions. The three objectives (operational cost, ENS, and failure cost) can thus be handled as non-commensurable and contradictory objectives of the multiobjective problem:

$$\min(F(x)) = \min\{f_1(x), f_2(x), f_3(x)\} \tag{6}$$

where $f_1(x)$, $f_2(x)$, and $f_3(x)$ are the operational cost, ENS, and failure cost of overall substation; x is the decision vector containing the potential maintenance schedules and extents over the scheduling horizon. Pareto-based multiobjective evolutionary algorithm NSGA II [29] is applied in the maintenance optimizer to optimize the maintenance schedules for this offshore power system. Pareto fronts give equal treatment to all objectives, which reach optima where none of the objectives can be further improved without degrading the others. A holistic view of the relationship among multiple objectives can be seen from the Pareto front. More details about the calculation of operational cost and failure cost, and implementation of NSGA II are given in [20], [28], [29].

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C. S. Chang obtained the Higher Diploma in electrical engineering from Hong Kong Polytechnic, the Diploma degree in electrical engineering from the Institution of Electrical Engineers, and the M.Sc. and Ph.D. degrees from the University of Manchester Institute of Science and Technology.

He is an Associate Professor in the Department of Electrical and Computer Engineering, National University of Singapore. His research includes the analysis and AI applications in power and traction systems.

Dr. Chang was Technical Chair of the Year 2000 IEEE Winter Power Meeting in Singapore. He was conferred the degree of D.Sc. by the University of Manchester Institute of Science and Technology in 2001.

Zhaoxia Wang received the B.S. degree in applied physics from East China University of Science and Technology and the M.Sc. and Ph.D. degrees from Nankai University, China.

From 2004 to 2008, she was an Associate Professor in the School of Electrical and Information Engineering, Tianjin University of Technology. From 2008 to 2011, she was a Researcher in the Department of Electrical and Computer Engineering, National University of Singapore. She is currently a Scientist in the Department of Computing Science, Institute of High Performance Computing, Singapore. Her current research interests include soft computing; intelligent algorithms and their applications; fuzzy theory and control; cross-disciplinary data mining and applications; fault detection and diagnosis; and system identification and optimization.

Fan Yang received the B.E. degree in hydro-electrical engineering from Huazhong University of Science and Technology (HUST), China, in 2005. Since then, she has been working toward the Ph.D. degree in electrical engineering from the National University of Singapore.

Her research mainly focuses on the maintenance optimization of substation in power systems using evolutionary algorithm.

W. W. Tan received the B.Eng. (electrical, honors) degree and the M.Eng. degree from the National University of Singapore in 1993 and 1995, respectively, and the D.Phil. degree from the University of Oxford, U.K., for her work on self-learning neurofuzzy control of nonlinear systems in 1997.

She then joined the University of Singapore, where she is currently an Associate Professor in the Department of Electrical and Computer Engineering. Her research program focuses on the application of systems science and computational intelligence paradigms for controller design, metrology, and fault detection and diagnosis. In particular, she has published papers on: i) intelligent modeling, control, and fault diagnosis using computational intelligence techniques; ii) application of advanced control algorithms to the semiconductor manufacturing industry; iii) microelectromechanical pressure sensors; and iv) auto-tuning of multivariable systems.

Dr. Tan received the FUZZ-IEEE 2005 Best Student Paper Award and FUZZ-IEEE 2006 Best Poster Presentation Award.