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Multi-Objective Optimal Placement of Sensors Based on Quantitative Evaluation of Fault Diagnosability

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ABSTRACT A multi-objective optimal sensor placement method based on quantitative evaluation of fault diagnosability is proposed. Fault diagnosability evaluation is the basis of fault diagnosis, and insufficient sensor point information is the main reason for the low quantitative evaluation index of fault diagnosability. Therefore, a method to improve the fault diagnosability of a system by adding soft and hard sensors is presented. However, increasing sensors is limited by the constraints of cost, reliability and complexity. In view of this and based on ensuring the fault diagnosability, a multi-objective optimization method for the sensors is proposed to improve system reliability and promote development towards stability, efficiency and economy.

INDEX TERMS Fault diagnosability, quantitative evaluation, sensor placement, NSGA-II.

I. INTRODUCTION

With the development of modern engineering systems towards scale, integration and complexity, the risk of failure also increases accordingly. Once the failure of such a system occurs, it will be difficult to detect and the loss will be immeasurable. Therefore, people put forward more urgent demands for high-security and reduced accident probability. The research shows that low fault diagnosability is one of the main reasons leading to a high failure rate for systems. That is to say, the measured information is not enough to support rapid and reliable fault detection. For research on fault diagnosability, the traditional methods mostly focus on qualitative research after a fault occurrence, which cannot quantify the true level of fault diagnosability [1]. Therefore, exploring how to evaluate the fault diagnosable performance of a system at the design stage (before failure occurs), and how to realize high fault diagnostic ability at the design stage through the optimal placement of sensors, is urgently needed.

The research on fault diagnosability mainly includes two aspects: diagnosability evaluation and diagnosability design. In recent years, the research on fault diagnosability evaluation mainly focuses on two aspects. First, fault diagnosability is regarded as a system characteristic, which is only related to the system property. Second, fault diagnosability is not only related to system attributes but also depends on the design of a fault diagnosis algorithm. Although the method of using a diagnosis algorithm to study fault diagnosability has been widely used, it is difficult to obtain an evaluation result that accurately reflects the diagnosability of the system because of its heavy dependence on the design accuracy of the residual error in the fault diagnosis process. Therefore, it is necessary to explore an effective method that can evaluate faults qualitatively and vectorize them in depth without relying on any fault diagnosis algorithm.

The research on the evaluation of fault diagnosability is aimed to provide the evaluation results of fault detectability and isolability under the existing system hardware conditions for a given set of faults. Literature [2] studies the fault diagnosability evaluation of linear systems based on the basic idea of model-based residual generation for fault diagnosis. Literatures [3]–[5] designed residuals using polynomial basis, equivalent space and coprime decomposition, and evaluated diagnosability according to the existence of residuals. However, the evaluation results of these traditional methods depend on the design accuracy of residual errors,

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which makes it difficult to accurately reflect the real diagnosable performance of the system. Literatures [6], [7] attempted to study diagnosability evaluation without relying on fault diagnosis algorithms, but these methods are deficient in two aspects: one is that they can only give qualitative analysis results and lack clear quantitative indicators, i.e. the degree of fault diagnosability; the other is that they do not consider uncertainties such as noise of non-linear systems, which seriously affects the accuracy of evaluation results. Recently, Lead Resercher's group at Linkping University in Sweden [8]–[10] used the Kullback-Leibler Divergence (KLD) method based on system characteristics to quantify the diagnosability of linear systems by measuring the similarity of the probability density function (PDF) under different fault conditions. Literature [9] only relied on its own linear system attributes, using the KLD method, to give the quantitative evaluation index of fault detectability and isolability. At the same time, literatures [11], [12] studied the fault sensitivity of nonlinear systems with this method, which provides a new basis for further quantitative evaluation of the nonlinear system fault diagnosability.

When the fault diagnosability evaluation index of the system is low, it is necessary to design the fault diagnosability to improve its evaluation index. Generally speaking, the fault diagnosability of the system can be satisfied by adding sensors to the system to increase the measurement information. The increase in measuring points can be hard sensors. However, due to considerations of installation space, cost and other factors, it is difficult to measure some important variables by hardware sensors. It is possible to estimate them by choosing other variables that are easy to measure, to form a mathematical relationship with them, and replace hardware (sensors) with soft sensors. Thus, the measurement information may be increased by adding hard sensors or soft sensors.

After designing the fault diagnosability, the evaluation index of fault diagnosability should be satisfied. However, because the position and quantity of the sensors added to the system are often subject to the structure and economic conditions of the system, it is important to consider the optimal placement of the sensors in order to improve the quality of the system [13]. At present, the research on optimizing sensor placement as a multi-objective optimization problem with the goal of improving fault diagnosability still needs further investigation [14].

The research on optimal placement of sensors began in the late 1970s. Since Lambert [15] used a fault tree to analyse the sensor placement based on the influence of fault sources on process variables, scholars have carried out extensive research on optimal sensor placement with abundant achievements [16]–[19]. Among them, the effective independent method and the modal kinetic energy method are the most widely used. From them, the effective independent coefficient method, the effective independent-driving point residue method and the random class algorithm are derived. Because optimal sensor placement involves many indicators, such as quantitative evaluation of faults, cost, accuracy and reliability, some scholars regard the optimal sensor placement as a multi-objective optimization problem and adopt a multi-objective evolutionary algorithm for research. Compared with the traditional method, the advantages of multi-objective evolutionary algorithms are that they can deal with non-linearity, discontinuity, non-differentiability, and do not need too much prior knowledge. So far, research on the multi-objective evolutionary algorithm has made some achievements, such as the VEGA algorithm [20], MOGA algorithm [21], NSGA algorithm [22], and SPEA algorithm based on elite retention strategy, etc. The NSGA-II algorithm based on fast sorting, density estimation and elite strategy is currently the best multi-objective optimization algorithm at [23]. Literature [24] uses the NSGA-II algorithm to solve the problem of residual sensors data allocation in the case of system failure. However, by analysing the above research results, we find that most of these studies are focused on quantitative research, that is, each sensor's contribution to fault diagnosability focuses on the qualitative evaluation of "yes" or "no", but lacks the quantitative analysis of sensor response to fault information.

Therefore, this paper explores an effective method to quantitatively evaluate the diagnosability of faults in non-linear systems. Based on the consideration of improving the fault diagnosis performance of the system by adding soft and hard sensors, the sensor placement is optimized using a multi-objective approach.

The remainder of the paper is organized as follows. Section II introduces a quantitative evaluation method for fault diagnosability. Section III discusses the design of soft sensors to increase the measurement information of the system. The multi-objective optimal sensors placement method is discussed in Section IV, which selected the optimal sensor configuration set of the system. Section V employs a vehicle power supply system model to demonstrate an optimal sensor placement problem. Finally, some conclusions are given in Section VI.

II. QUANTITATIVE EVALUATION OF FAULT DIAGNOSABILITY

A. PROBLEM DESCRIPTION

Consider a system that needs to be evaluated for fault diagnosability:

$$\begin{aligned} \dot{x} &= g(x, u, v, f) \\ y &= h(x, u, w) \end{aligned} \tag{1}$$

where $x \in R^n$ is the state vector of the system, $y \in R^m$ is the output of the system, $u \in R^q$ is the input function, g and h are non-linear functions, v and w are the state noise and measurement noise of the known PDFs, and f is the possible faults in the system. The system described in Eq. (1) is a typical non-linear structural system. In order to study the optimal placement of sensors, Eq. (1) can be defined as a system model or a system structure model.

Since the residual is the basis of fault diagnosis, the common method is to compare the actual output y and expected output $\hat{y}$ of the observation system to form a residual, and then extract fault features from the residual to determine whether the system has a fault. The residual of the system can be expressed as:

$$r = y - \hat{y} \tag{2}$$

In theory, when there is no fault in the system, the residual is zero. When the system fails, the residual deviates from zero, based on which the system fault diagnosis can be carried out. However, due to the influence of uncertainties such as random noise, the PDF of the residual r should be close to the PDF of the measurement noise w when the system does not fail. If there is a deviation from the PDF of w, the system will fail.

Thus, in order to quantitatively evaluate the fault diagnosability of system (1), an effective method is to quantitatively describe the detectability and isolability of different faults by measuring the difference in PDF. In probability theory, the KLD method, also known as relative entropy, is an effective method to describe the difference between two probability distributions. Therefore, it is undoubtedly feasible to quantitatively evaluate the diagnosability of faults using KLD, which can measure the diversity of a multivariate distribution when different faults occur.

B. QUANTITATIVE EVALUATION OF FAULT DIAGNOSABILITY BASED ON KLD

Assuming that there are two different faults f_i and f_j in the system, considering the influence of the faults on the system, the residual will be different under these two faults. Therefore, the difference in residual can be considered to distinguish the two kinds of faults. It is assumed that under these two typical faults, the PDFs of residual are $p_i \in Y_{f_i}$ and $p_j \in Y_{f_j}$ respectively, where Y_{f_i} and Y_{f_j} are the PDF set of residuals under faults. According to the theory of data similarity, the greater the difference between p_i and p_j, the greater the difference between the corresponding residual, which means that the two kinds of residual data are easier to separate.

In order to verify the above analysis, the following likelihood functions are introduced:

$$\lambda(r) = \log \frac{p_i(r)}{p_j(r)} \tag{3}$$

where p_i is the PDF of the residual when fault f_i occurs, p_j is the PDF of the residual when fault f_j occurs and $\lambda(r)$ is the defined likelihood function.

According to the logarithmic characteristics of the likelihood function in Eq. (3), it is not difficult to find that when only fault f_i occurs in the system, the PDFs of the residuals satisfy $p_i > p_j$, and the likelihood function follows $E[\lambda(r)] > 0$; conversely, when only fault f_j occurs in the system, the PDFs of the residuals satisfy $p_i \leq p_j$, and the likelihood function follows $E[\lambda(r)] \leq 0$. $E[\lambda(r)]$ can judge the different types of faults occurring in the system by changing its symbols. The value of $E[\lambda(r)]$ represents the probability of occurrence of a fault, which also indicates the difficulty of distinguishing the fault from other fault forms. Its expression is:

$$E[\lambda(r)] = E\left[\log \frac{p_i(r)}{p_j(r)}\right] \tag{4}$$

Eq. (4) can be found to satisfy the calculation formula of KLD.

$$K(p_i||p_j) = \int_{-\infty}^{\infty} p_i(r) \log \frac{p_i(r)}{p_j(r)} dr = E_{p_i}\left[\log \frac{p_i}{p_j}\right] \tag{5}$$

Here, the minimization of KLD is used to quantitatively evaluate fault detectability $FD(f_i)$ and fault isolability $FI(f_i, f_j)$, which can be obtained by the following equations:

$$FD(f_i) = \min[K(p_i||p_{NF})] \tag{6}$$

$$FI(f_i, f_j) = \min[K(p_i||p_j)] \tag{7}$$

where p_{NF} is the density function of the system residual probability when the system is normal, which is equivalent to the PDF of the measurement noise to which the system is subjected. Since $K(p_i||p_j) \geq 0$, $FD(f_i) \in (0, \infty)$. Thus, the larger $FD(f_i)$ is, the less difficult it is to detect fault f_i. When $FD(f_i) = 0$, fault f_i cannot be detected. Similarly, the larger $FI(f_i, f_j)$ is, the stronger the isolability between fault f_i and f_j; when $FI(f_i, f_j) = 0$, faults f_i and f_j do not have isolability.

By applying the quantitative evaluation method of fault detectability in Eq. (6) and (7), effective evaluation of fault detectability and isolability can be achieved. However, in the application of this method, it is necessary to know the PDF of residuals. For the estimation of residual PDF, the kernel density estimation (KDE) method is usually used. In order to ensure the accuracy of estimation, a large amount of data is usually employed for estimation. Therefore, for the purpose of improving computational efficiency, a sparse kernel density estimation (SKDE) method is more advantageous [25]. This method has the advantages of fast calculation speed, small memory requirement, and more smooth and accurate estimation of PDF.

By using the SKDE method mentioned above, the PDF $p(r)$ of the residual can be estimated. For Eq. (5) in a nonlinear structure, the Monte Carlo (MC) method can be used to approximate the solution.

Taking the process of solving Eq. (5) as an example, the MC method is used to obtain the solution:

$$\hat{K}(p_i||p_j) = \frac{1}{n_s} \sum_{n_s} \log \frac{\hat{p}_i}{\hat{p}_j} \tag{8}$$

where n_s is the number of $\hat{p}_i$ sampled from p_i. According to [26], the estimated error in Eq. (8) usually obeys a normal distribution, the expectation is 0 and the variance is:

$$\sigma_{MC}^2 = \frac{1}{n_s}\left(E\left[\log\left(\frac{\hat{p}_i}{\hat{p}_j}\right)\right]^2\right) \tag{9}$$

That is to say, the estimation error satisfies $\tilde{r} \sim N(0, \sigma_{MC}^2)$, with the increase of sampling number n_s, the variance of MC estimation will also decrease.

III. SOFT SENSOR DESIGN

To ensure that the system meets the requirements of fault detectability and isolability, it is necessary to obtain enough measurement information in the system, and the acquisition of measurement information requires the configuration of sufficient sensors. Of course, based on the traditional method, the addition of hard sensors can increase the measurement information of the system. But the problem that cannot be ignored is that because of the limitations of installation space, technology and cost in the system design, it is difficult and uneconomical to obtain all the measurement data from hard sensors. A feasible method is to replace these hard sensors with software (soft sensors) by establishing the mathematical relationship between the variables to be measured and those already measured. In order to distinguish, soft sensors and hard sensors are collectively called measuring point sensors (MPS).

Let the number of configurable hard sensor nodes in the system be n_0, the set of configured hard sensors be $S_0 = \{s_1, s_2, \cdots, s_{n_0}\}$, and the measurement information of sensors be $x_1, x_2, \cdots, x_{n_0}$. If there is a redundant configuration of sensor s_i in the system, that is, measurement data of sensor s_i can be expressed mathematically by metrical data of other sensors configured in the system, then there should be a relationship:

$$\hat{x}_i = g(x_1, x_2, \cdots, x_{i-1}, x_{i+1}, \cdots, x_m, d) \tag{10}$$

where $x_1, x_2, \cdots, x_{i-1}, x_{i+1}, \cdots, x_m$ is the measurement data vector of the hard sensor. $\hat{x}_i$ is the soft sensor, which is the ith sensor data point fitted by the measurement data of other sensors. d is the measurable disturbance information. g is the describing function of analytic redundancy relationship. In order to design soft sensors to replace the original hard sensors, the key is to use the algorithm to construct the description function g.

The partial least square (PLS) method can extract redundant and highly correlated data through spatial compression technology, overcome the correlation between noise and variables, and accurately capture the mathematical relationship between sensor data. The redundancy relationship between sensors can be obtained using the PLS method. Although traditional PLS can extract useful information from high-dimensional data and is suitable for finding process quality characteristics and establishing models from large amounts of data, the essence of PLS is the linear regression method. Thus, the modelling accuracy is not high when dealing with data with strong non-linearity. Therefore, in this paper, the improved kernel partial least square (KPLS) method is employed to construct the redundancy relationship between sensors. Based on the kernel function, the input space is mapped to high-dimensional feature space through the non-linear function $\phi()$, thus the non-linear relationship between the input space and the output space can be obtained.

When using KPLS for redundancy analysis, the input data matrix is $X = [x_1, x_2, \cdots, x_m]$, which consists of the data of m sensors. The output variable is $Y = \hat{y}$, which is the data collected by the redundant sensor s_j.

Since the mean value of mapping data is zero in the KPLS algorithm, it is necessary to centralize the core matrix K. For the $N \times N$-dimensional core matrix K, the centralization process is as follows:

$$\tilde{K} = K - I_n K - K I_n + I_n K I_n \tag{11}$$

where $I_n = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix}$

After selecting the kernel function, the KPLS algorithm can be completed using the following steps

Step 1: Set $i = 1, K_i = K, Y_i = Y$;

Step 2: Initialize u_i, let u_i equal any column of Y_i;

Step 3: Calculate the output space variable score vector $t_i = K_i u_i$, $t_i \leftarrow t_i / \|t_i\|$;

Step 4: Calculate the output space variable score weight vector $q_i = Y_i^T t_i$;

Step 5: Loop computing the input space variable score vector $u_i = Y_i q_i$, $u_i \leftarrow u_i / \|u_i\|$;

Step 6: Repeat Steps 2 to 5 until convergence. The convergence condition is that t_i and t_{i-1} are equal in the allowable error range;

Step 7: Update matrices K and Y according to the following equations

$$\begin{aligned} K_{i+1} &= K_i - t_i t_i^T K_i - K_i t_i t_i^T + t_i t_i^T K_i t_i t_i^T \\ Y_{i+1} &= Y_i - t_i t_i^T Y_i \end{aligned}$$

Step 8: Let $i = i + 1$, terminate the loop if $i > i_{\max}$, and return to Step 2.

The application of KPLS and the method to determine the number of potential variables are detailed in the literature [27], [28].

When the relationship between sensors is found using the KPLS method, the analytical redundancy model between sensors can be obtained.

As mentioned above, the set of hard sensors in the system is S_0, and the KPLS method can be used to express the hard sensors in S_0 mathematically. However, not all hard sensors in S_0 can be replaced by soft sensors. If n_1 of all n_0 sensors in S_0 can be expressed mathematically, a set of soft sensor configuration S_1 can be constructed, then the set of all the MPS in the system is:

$$S = S_0 \cup S_1 \tag{12}$$

It is not difficult to find that there are n sensors in set S, and they satisfy $n = n_0 + n_1$.

The set S of MPS includes both hard sensors and soft sensors. Although they can provide measurement information for the system, their cost-effectiveness is not the same when considering the cost, reliability and complexity. Therefore, it is necessary to reconfigure the sensor set to realize the optimal design of S.

IV. MULTI-OBJECTIVE OPTIMAL PLACEMENT OF MPS

A. CONSTRAINT FUNCTION IN OPTIMAL PLACEMENT OF MPS

Due to the constraints of installation space, technology and cost, the following four constraints are given for the sensor placement.

1) Limitation of the number of hard sensors. If the set of hard sensors in the system is $S_0 = \{s_1, s_2, \cdots, s_{n_0}\}$, the number of hard sensors in the set should satisfy:

$$n_0 \leq q \tag{13}$$

where q is the upper limit of the number of hard sensors, and the selection of q should be determined according to the actual system requirements.

2) The existence of soft sensors. Considering the analytic redundancy between sensors, soft sensors can be used to replace hard sensors. However, a problem that cannot be ignored is that after the optimal configuration of the sensor, there may be a deletion of the hard sensor. If the removed hard sensor is used to construct the soft sensor, the soft sensor will not exist. Therefore, in the optimization process, the existence of a soft sensor should be considered as a constraint condition, and it should satisfy the following equation:

$$s_{i0} = g(s_j, s_{j+1}, \cdots, s_{j+m}) \quad s_j, s_{j+1}, \cdots, s_{j+m} \neq 0 \tag{14}$$

where s_{i0} is a soft sensor to be reconstructed, $s_j, s_{j+1}, \cdots, s_{j+m}$ are hard sensors used to reconstruct s_{i0}, and g is a non-linear function.

3) The constraint on fault detectability. Fault detectability is the basis of fault detection, and sufficient information from sensors is the premise to ensure fault detectability. Therefore, the constraint of fault detectability should be considered in the configuration of sensors.

If the set of all the sensors in the system is S, and all the sensors in S are configured in the system, the fault detectability of the system can be maximized

$$FD_{\max}(f_i) = K_S(p_i || p_{NF}) \tag{15}$$

where $K_S(p_i||p_{NF})$ is the detectability of fault f_i for a given set of sensors S. In fact, in order to ensure that fault f_i can be detected, it is not necessary to configure all sensor points. If the optimal allocation of measuring points is considered, it should be satisfied:

$$K_S(p_i||p_{NF}) \geq K_{req}(p_i||p_{NF}) \tag{16}$$

where $K_{req}(p_i||p_{NF})$ is the minimum requirement of fault detectability. Under this basic requirement, the set S_{req} of sensors should be a subset of set S.

4) The constraint on fault isolability. Fault isolability is the basis of fault isolation. Compared with fault detection, fault isolation is more complex. It requires not only that faults can be detected, but also that enough information can be obtained so that different faults can be isolated and diagnosed.

For all the sensors S in the system, when the measurement information is acquired, the maximum quantified evaluation index of fault isolability under the current situation can be achieved:

$$FI_{\max}(f_i, f_j) = K_S(p_i||p_j) \tag{17}$$

where $K_S(p_i||p_j)$ is a quantitative evaluation index for the isolability of fault f_i and f_j under set S of sensors. In order to achieve the minimum requirement of fault isolability $K_{req}(p_i||p_j)$, similar to the fault detectability constraint, it should be satisfied.

$$K_S(p_i||p_j) \geq K_{req}(p_i||p_j) \tag{18}$$

B. OBJECT FUNCTION IN OPTIMAL PLACEMENT OF MPS

After designing the constraints function of the optimization process, the objective function is also needed in the process. Here we define three objective functions.

Definition 1 : Under set S of MPS, the relative cost of sensors C_s is defined as the cost coefficient under set S.

$$C_s = 0.1 + \left[\sum_{i\in n}(\mu_i c_i s_i)\right] \Big/ n \tag{19}$$

where n is the total number of MPS. c_i is the cost coefficient of the sensor s_i. c_i is mainly composed of the price of the sensor itself, the installation cost and the later maintenance cost. μ_i is the cost quantification factor. If the current MPS is a hard sensor, it satisfies $\mu_i = 1$. However, if it is a soft sensor, it satisfies $\mu_i = 0.6$.

Remark: The set of MPS is $S = \{s_1, s_2, \cdots, s_n\}$. For a sensor $s_i \in S$, if the sensor is selected, $s_i = 1$, otherwise $s_i = 0$. The cost quantification factor μ_i is introduced considering the later maintenance cost of the soft sensor. The purpose is to differentiate soft and hard sensors, and then design the objective function in accordance with the actual situation.

Definition 2 : Under set S of the MPS, the reliability index of the sensor is defined as R_s:

$$\begin{aligned} R_s &= 1 - (\max_{\forall i} U_i) \\ U_i &= \pi_i \cdot (r_i)^{s_i} \end{aligned} \tag{20}$$

where U_i is the probability that fault f_i cannot be detected, π_i is the prior probability of fault f_i and r_i is the failure probability of the sensor.

Remark: It can be seen from Eq. (20) that the greater the R_s, the higher the reliability of the candidate sensor. But the same R_s may also represent different sets of sensors.

Definition 3: Because the sensor may be a hard sensor or soft sensor, in view of the difficulty of its configuration in the system, the implementation complexity of the sensor in the system is defined as:

$$T_s(n) = \eta_i \cdot O(f(n)) + 0.1 \tag{21}$$

where $O()$ is an order of magnitude function, $f(n)$ is a function of the same order of magnitude as $T_s(n)$ and satisfying $\lim_{n\to\infty} T_s(n)/f(n) = C$, C is a constant that is not zero and η_i is the symbol function. If the current MPS is a hard sensor, $\eta_i = 0$; otherwise, if it is a soft sensor, $\eta_i = 1$.

C. MULTI-OBJECTIVE OPTIMAL PLACEMENT MODEL OF MPS

From the above analysis, the optimal placement of sensors is a multi-objective optimization problem that integrates the factors of fault detectability, fault isolability, cost, reliability and complexity. The problem can be described as:

$$\begin{aligned}
&\{\min C_s, \max R_s, \min T_s\}\\
&s.t.\ n \le q\\
&\qquad \text{Existence conditional equation (14)}\\
&\qquad K_S(p_i||p_{NF}) \ge K_{req}(p_i||p_{NF})\\
&\qquad K_S(p_i||p_j) \ge K_{req}(p_i||p_j)
\end{aligned} \tag{22}$$

The constraints are the total number of hard sensors, the existence of soft sensors, and the quantitative evaluation index of fault detectability and isolability. Under the premise of satisfying these optimization constraint functions, we try to find the optimal set of MPS, so that the reliability of sensor placement is as high as possible, while the cost and complexity are as low as possible. In order to solve the multi-objective optimization problem in Eq. (22), this paper intends to adopt the improved NSGA-II algorithm to optimize the sensor placement.

D. IMPROVED NSGA-II OPTIMIZATION ALGORITHM

NSGA-II is one of the most popular multi-objective genetic algorithms at present. It can reduce the complexity of the non-inferior ranking genetic algorithm, has the advantages of fast running speed and good convergence of solution set. Thus, it becomes the performance benchmark of other multi-objective optimization algorithms.

In order to solve the multi-constrained and multi-objective function problem shown in Eq. (22) using the NSGA-II method, it is necessary to improve the algorithm of NSGA-II. The main purpose of the improvement is to ensure that the quantitative evaluation indexes of fault detectability and isolability can be satisfied in the optimization process. The flow chart of the improved NSGA-II algorithm is shown in Fig. 1. The steps of the improved NSGA-II algorithm are described as follows:

Step 1: Let the iteration number be G, the rank number is $Rank$, and randomly generate the initial population $P_0(t)$ with a size of N_G.

Step 2: Determine whether the individual chromosomes in the population satisfy the condition of fault detectability and isolability, and if not, regenerate the population.

Step 3: Determine whether the calculation of population congestion and the registration order have been completed and if it has been completed, transfer to Step 4, otherwise to Step 2.

Step 4: Fast non-dominant population sorting. First, the first level non-inferior population is determined according to the value of the objective function. Then, the first level individuals are moved out of the population. In the remaining population, the new non-inferior solution is determined by the same method, which is defined as rank 2. Repeat by analogy, until all individuals are assigned their corresponding ranks.

Step 5: Computation of crowding density for individuals belonging to the same non-inferior rank.

Step 6: Make a tournament selection to determine the new population. Two chromosomes were randomly selected from the population for rank comparison, and individuals with smaller rank were selected. If the two have the same grade, the individuals with smaller density are selected. Thus, population $pop_1(t)$ can be formed.

Step 7: Carry out adaptive crossover and mutation to generate an offspring population $Q(t)$. Individual fault detectability and isolability should be guaranteed in crossover and mutation operations.

Step 8: Merge population $P(t)$ and $Q(t)$ to form a new population.

Step 9: Generate a new generation of population NP_t using the elite strategy.

Step 10: The number of iterations is judged. If the number of iterations is limited, the result will be output, and the cycle will end. Otherwise, it will go to Step 2.

In order to ensure the basic requirements of fault detectability and isolability in the process of optimizing the placement of sensors, the filter module of fault detectable and separable is added in the process of optimizing. Specifically as follows:

1) Since the optimal placement of the sensors is an integer programming problem, the placement vector of the sensor can be directly used as the chromosome coding scheme.

2) As shown in Fig. 1, the detectable and separable filter module are mainly designed to satisfy constraints Eq. (16) and (18) in the multi-objective optimization process. When the population initialization process detects that the individual chromosome does not satisfy the quantitative evaluation index of fault diagnosability, it is necessary to regenerate the individual population. In the process of chromosome crossover and mutation, if the chromosome does not change before and after crossover and mutation, or the chromosome after crossover and mutation do not satisfy the restriction conditions of fault diagnosability, the current crossover and mutation will be invalid.

V. SIMULATION

A. VEHICLE POWER SUPPLY SYSTEM

In this paper, a 120 kW military vehicle power supply system (VPSS) was used as the simulation object and its core component is a diesel generator set, as shown in Fig. 2. Under the condition of field operation, the VPSS is not only the main energy source of modern weapons and equipment but also provides a safe and reliable life guarantee for the daily use of electricity in the army. The system mainly includes an automobile chassis, a noise reduction chamber, and a 120 kW diesel generator set and its control system. The diesel engine is a Cummins NT855-GA, the electronic governor is a Cummins, the synchronous generator is a Stanford UCI274F, and the voltage regulator is an MX321 excitation control system. The relationship between the modules is shown in Fig. 3.

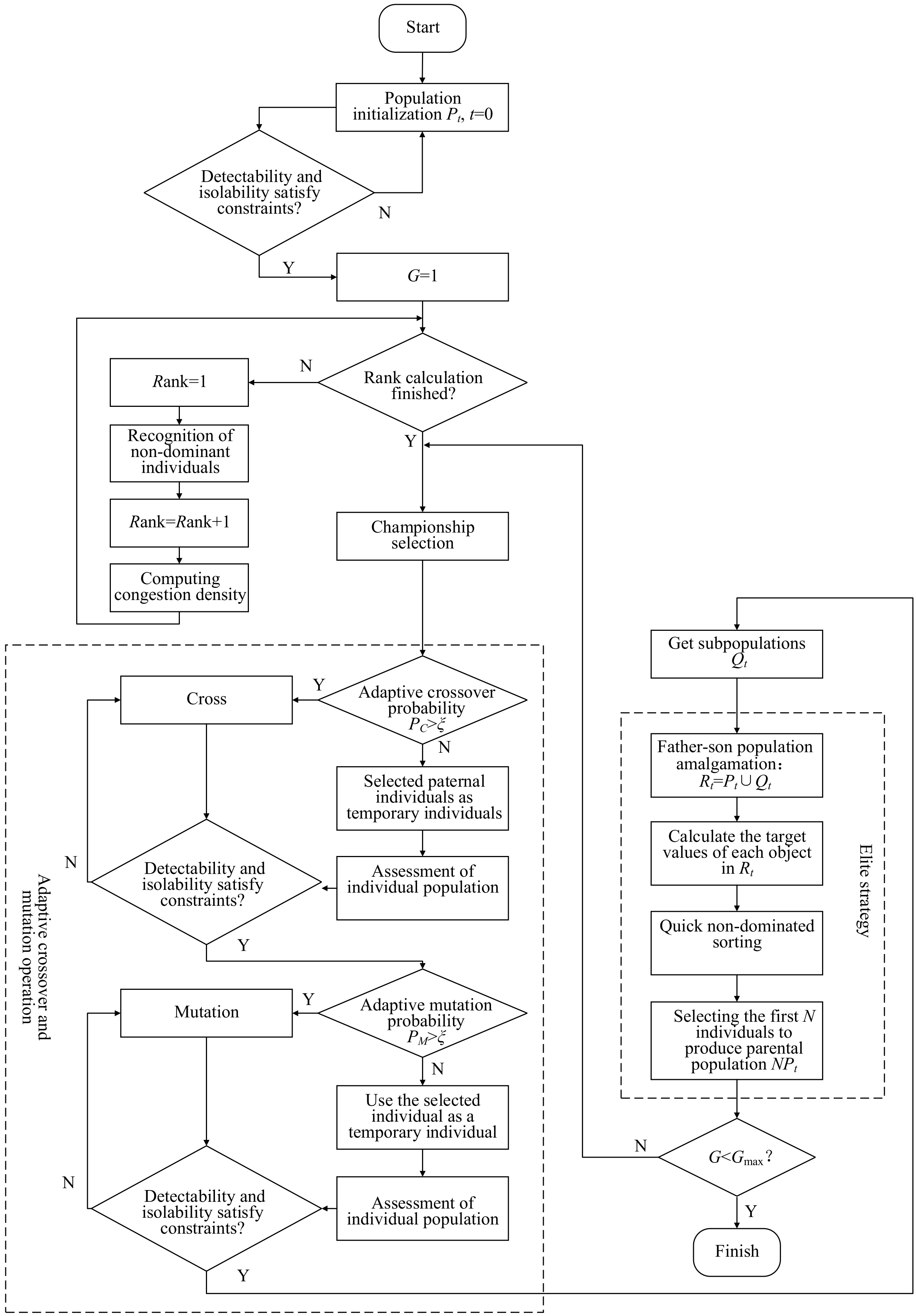

FIGURE 1. Flow chart of the improved NSGA-II algorithm.

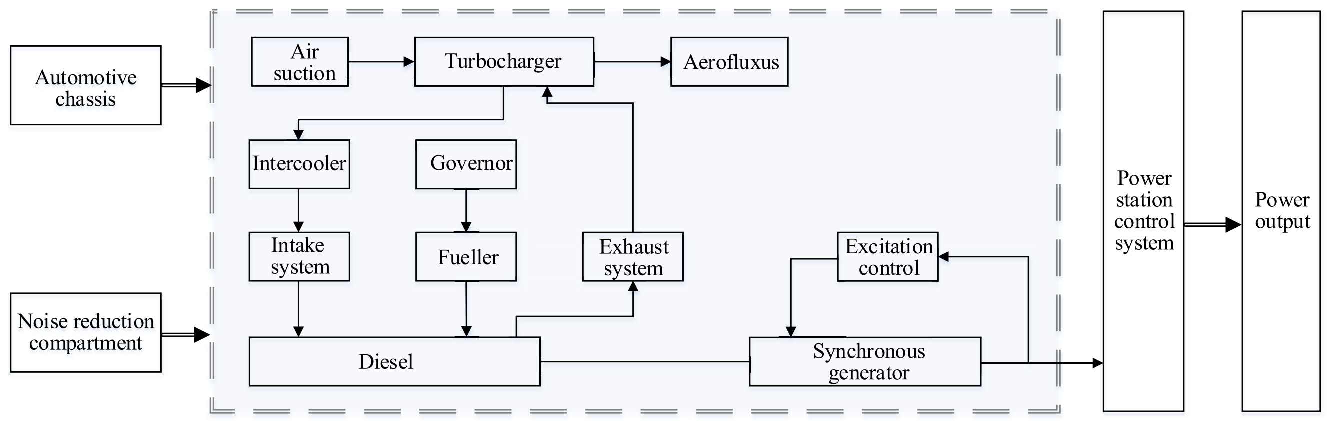

FIGURE 2. Structural chart of VPSS.

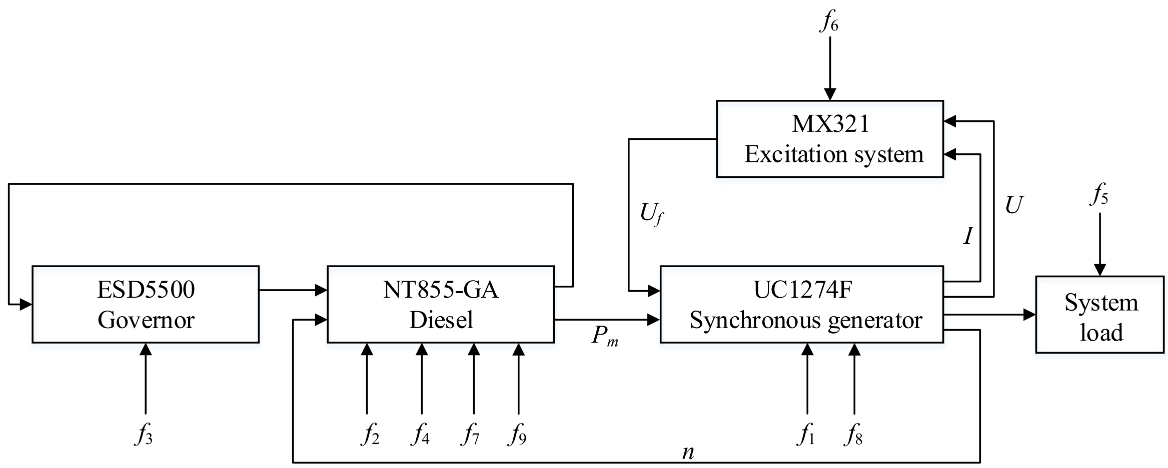

FIGURE 3. Module diagram of VPSS.

TABLE 1. Common VPSS faults.

Fault	Fault Description
f_1	Generator excitation loss
f_2	Diesel filter blockage
f_3	Governor regulation failure
f_4	Intercooler failure
f_5	System overload
f_6	Excitation module failure
f_7	Injector failure
f_8	Insufficient output power
f_9	Engine surge

TABLE 2. Qualitative evaluation of fault diagnosability.

	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8
f_1	0	0	0	1	0	1	0	0
f_2	0	0	0	0	0	1	0	0
f_3	1	0	0	0	1	0	1	0
f_4	0	0	1	0	0	1	0	0
f_5	0	1	1	0	0	0	0	0
f_6	1	1	0	0	0	1	0	1
f_7	0	0	0	0	0	1	0	0
f_8	0	1	0	0	0	0	0	0
f_9	1	1	0	0	0	1	0	0

Based on theoretical analysis, the mathematical model of the 120kW VPSS was established using block modelling. Then, a 120kW vehicle power supply simulation system was built on the MATLAB/Simulink platform by comparing the simulation experiment with the real experiment data, setting parameters and introducing boundary constraints.

Where vector U is the d-axis and q-axis voltage of the generator. I is the d -axis and q -axis current of the generator. U_f is the excitation voltage. P_m is the mechanical power of the generator. n is the speed of the generator, and the rated output voltage of the generator is 400V. Table 1 shows some types of faults that may occur during operation of the VPSS, all 9 failures are permanent faults.

The VPSS state was detected by sensors, and the VPSS fault state was judged by detecting whether the measured

TABLE 3. Quantitative evaluation of fault diagnosability.

	FD	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
f_1	0.3462	0	0.1298	0.8978	0.1290	0.1432	0.2765	0.0988	0.3049	0.1583
f_2	0.4387	0.1304	0	0.8070	0.9908	0.1435	0.2787	0	0.2230	0.4330
f_3	0.2122	0.9029	0.7865	0	0.7434	0.4634	0.4172	0.8432	0.7729	0.9533
f_4	0.3456	0.1300	0.8990	0.7321	0	0.6432	0.7432	0.8432	0.6032	0.6633
f_5	0.6783	0.1765	0.1543	0.4764	0.7325	0	0.3434	0.1088	0.1920	0.4900
f_6	0.5435	0.2910	0.2898	0.4278	0.7000	0.3299	0	0.5898	0.2011	0.1003
f_7	0.7646	0.0910	0	0.1022	0.7853	0.0987	0.5786	0	0.8833	0.4022
f_8	0.6020	0.4430	0.3350	0.8800	0.5300	0.1822	0.1987	0.7921	0	0.5290
f_9	0.7233	0.1033	0.3900	0.9233	0.7320	0.5520	0.0977	0.3800	0.4910	0

data from sensors is abnormal. In this example, all the state variables that can be detected were regarded as possible sensor points. The data detected by sensors in the system were voltage (V), current (I), fuselage temperature (T), power factor (ϕ), frequency (F), load (P), engine speed (V_s) and excitation voltage (U_0). The sensors used in VPSS are the common types of power system. Because of the non-linear characteristics of VPSS, when a fault occurs, the measured data will fluctuate in a certain range.

B. FAULT DIAGNOSABILITY EVALUATION OF VPSS

In order to achieve the purpose of system fault diagnosis, eight residual variables $r_i, i = 1, 2, \cdots, 8$ were defined according to the measured sensor data. Combined with the faults described in Table 1, the fault feature library was established. And the influence of faults on the residual was represented by the fault feature matrix. The "binary method" $\{1, 0\}$ was used to describe the change of residual, "0" means that the fault has no effect on the residual, and "1" means that the fault makes the residual deviate. Through the detection of nine kinds of faults, the description matrix of fault characteristics was obtained as shown in Table 2.

In Table 2, the change of residual caused by faults is qualitatively analysed. In order to quantitatively analyse nine possible VPSS faults and further optimize the placement of sensors, the quantitative evaluation results of fault diagnosability can be obtained using the KLD method proposed in Section II, as shown in Table 3.

Comparing the qualitative analysis of Table 2 with the quantitative analysis of Table 3, the conclusions of fault diagnosability evaluation are consistent: 1) All nine kinds of fault can be detected; 2) In all nine kinds of detectable faults, faults f_2 and f_7 cannot be isolated from each other.

C. MULTI-OBJECTIVE OPTIMAL PLACEMENT OF MPS IN VPSS

Based on the quantitative evaluation of VPSS fault diagnosability, the multi-objective optimal method was used to configure the sensors of the system. By analysing the VPSS test data, eight measurable state variables $S_0 = \{V, I, T, \phi, F, P, V_s, U_0\}$ were detected in the system, which can be regarded as eight hard sensors in the system. Quantitative evaluation of fault diagnosability for nine possible fault modes in the system was also carried out around these eight state variables.

Considering the complexity, cost, maintenance cycle and other factors of hard sensors, combined with the analytic redundancy relationship between hard sensors, soft sensors can be considered to replace hard sensors to ensure that the system can obtain enough information from measurement points.

By analysing the measurement history data of eight hard sensors and using the KPLS method in Section III, it was determined that the power factor (ϕ), system load (P) and engine speed (V_s) can be fitted by other hard sensor measurement data. That is to say, the three hard sensors can be replaced by soft sensors $S_1 = \left\{\hat{\phi}, \hat{P}, \hat{V}_s\right\}$. Therefore, the set of all sensor points in the system is

$$\begin{aligned} S &= S_0 \cup S_1 \\ &= \left\{V, I, T, \phi, F, P, V_s, U_0, \hat{\phi}, \hat{P}, \hat{V}_s\right\} \\ &= \{s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8, s_9, s_{10}, s_{11}\} \end{aligned} \tag{23}$$

In order to optimize the sensor set S, according to the objective function in the process of sensor optimization, it is necessary to determine the cost coefficient c_i, the reliability index r_i and the complexity factor $O(f(n))$, as shown in Table 4. The cost factor c_i is measured by the actual cost of hardware equipment. The reliability index r_i is estimated by experience. The complexity of soft sensors is obtained by the complexity of algorithm design.

After determining the constraint function and the objective function, the improved NSGA-II algorithm was used to optimize the placement of the sensors based on multi-objective method.

In the optimization process, there are eleven sensor points in the system, namely eight hard sensors and three soft sensors. However, not all eleven sensors are needed to ensure that the fault diagnosability evaluation index meets the requirements. Here we used 60% of the quantitative evaluation index of fault diagnosability as the expected value to optimize the sensors. As shown in Table 5, the optimal placement of

TABLE 4. Cost coefficient, failure probability and complexity factor of MPS.

Sensor Point	c_i	r_i	$O(f(n))$
s_1	0.8	0.01	0
s_2	0.8	0.02	0
s_3	0.3	0.03	0
s_4	1.0	0.01	0
s_5	0.9	0.02	0
s_6	0.8	0.01	0
s_7	0.5	0.05	0
s_8	1.0	0.04	0
s_9	0.1	0	0.5
s_{10}	0.1	0	0.6
s_{11}	0.1	0	0.8

TABLE 5. Optimal placement results of MPSs.

C_s	R_s	T_s	S
0.8200	0.9885	0.1000	$\{V,I,T,F,P\}$
0.6720	0.9026	0.9000	$\{V,I,T,F,\hat{V}_s\}$

sensors for the Pareto frontier solution is satisfied. Considering the Pareto set optimization method adopted in [29], the optimal sensor configuration of VPSS can be selected.

Both results in Table 5 belong to the Pareto frontier solution. In order to reflect the role of soft sensors in the system and many comprehensive factors that we have not considered, the optimal configuration set of sensors is selected as $S_{opt} = \left\{V, I, T, F, \hat{V}_s\right\}$. That is to say, for all the sensors in VPSS, only five sensor points, including voltage (V), current (I), fuselage temperature (T), frequency (F) and engine speed ($\hat{V}_s$), can be selected to satisfy the quantitative evaluation index of fault diagnosability. Additionally, the optimized sensor set took into account the cost, reliability and complexity factors of the system, so as to realize the optimal placement of the sensors.

VI. CONCLUSION AND FUTURE PROSPECTS

Research on fault diagnosability mainly includes two aspects: fault diagnosability evaluation and fault diagnosability design. Based on the quantitative evaluation of fault diagnosability, the problem of optimal placement of sensors is studied in this paper. Although the method described in this paper can obtain the optimal sensor configuration set by optimizing the quantitative evaluation of fault diagnosability, the following three problems need to be further studied:

1) For a fault system with known model structure, how many sensors should be deployed in order to make all possible faults of the system detectable and separable. Where and how many sensors should be deployed when the existing sensors in the system are insufficient?

2) In the case study, the criteria for selecting the optimal sensor set are as follows: the optimal fault diagnosability quantification index reaches 60% of the maximum fault diagnosability quantification index of the system. So, what is the best quantitative index for fault diagnosability?

3) When the system is affected by uncertainties such as noise and disturbance, the residual could not be a reflection of fault information. At this time, the PDF of residual and even the quantitative index of fault diagnosability will change accordingly. What impact will these changes have on the fault diagnosability, and will the optimal sensor placement set change accordingly?

These problems are not only related to the problem of fault diagnosability evaluation, but also the need to consider how to synthesize fault diagnosability evaluation and fault diagnosability design. At the beginning of system design, fault diagnosability should be taken into the system design as an intrinsic performance since it will then provide a strong guarantee for the safe and reliable operation of the system, which will be a very meaningful subject and the direction of our next efforts.

REFERENCES

[1] S. Florin, P. Felix, P. Ionela, and S. Stefan, "Hierarchical control with guaranteed fault diagnosability," *IFAC-PapersOnLine*, vol. 51, no. 24, pp. 1105–1110, 2018.

[2] F. Fu, D. Wang, P. Liu, and W. Li, "Evaluation of fault diagnosability for networked control systems subject to missing measurements," *J. Franklin Inst.*, vol. 355, no. 17, pp. 8766–8779, 2018.

[3] M. Nyberg and L. Nielsen, "Parity functions as universal residual generators and tool for fault detectability analysis," in *Proc. 36th IEEE Conf. Decis. Control*, San Diego, CA, USA, Dec. 1997, pp. 4483–4489.

[4] E. Y. Chow and A. S. Willsky, "Analytical redundancy and the design of robust failure detection systems," *IEEE Trans. Autom. Control*, vol. AC.-29, no. 7, pp. 603–614, Jul. 1984.

[5] E. Frisk and M. Nyberg, "A minimal polynomial basis solution to residual generation for fault diagnosis in linear systems," *Automatica*, vol. 37, no. 9, pp. 1417–1424, 2001.

[6] L. K. Carvalho, M. V. Moreira, and J. C. Basilio, "Diagnosability of intermittent sensor faults in discrete event systems," *Automatica*, vol. 79, pp. 315–325, May 2017.

[7] L. Trave-Massuyes, T. Escobet, and X. Olive, "Diagnosability analysis based on component-supported analytical redundancy relations," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 36, no. 6, pp. 1146–1160, Nov. 2006.

[8] J. Åslund, E. Frisk, and D. Jung, "Asymptotic behavior of a fault diagnosis performance measure for linear systems," *Automatica*, vol. 106, pp. 143–149, Aug. 2019.

[9] D. Eriksson, E. Frisk, and M. Krysander, "A method for quantitative fault diagnosability analysis of stochastic linear descriptor models," *Automatica*, vol. 49, no. 6, pp. 1591–1600, 2013.

[10] D. Jung, L. Eriksson, E. Frisk, and M. Krysander, "Development of misfire detection algorithm using quantitative FDI performance analysis," *Control Eng. Pract.*, vol. 34, no. 34, pp. 49–60, 2015.

[11] S. Eguchi and J. Copas, "Interpreting Kullback–Leibler divergence with the neyman–pearson lemma," *J. Multivariate Anal.*, vol. 97, no. 9, pp. 2034–2040, 2006.

[12] J. Harmouche, C. Delpha, and D. Diallo, "A theoretical approach for incipient fault severity assessment using the Kullback-Leibler Divergence," in *Proc. 21st Eur. Signal Process. Conf.*, Sep. 2013, pp. 1–5.

[13] D. Eriksson, M. Krysander, and E. Frisk, "Using quantitative diagnosability analysis for optimal sensor placement," in *Proc. 8th IFAC Symp. Fault Detection, Supervis. Safety Techn. Process.*, 2012, vol. 45. no. 20, pp. 940–945.

[14] F. Domingo-Perez, J. L. Lazaro-Galilea, A. Wieser, E. Martin-Gorostiza, D. Salido-Monzu, and A. de la Llana, "Sensor placement determination for range-difference positioning using evolutionary multi-objective optimization," *Expert Syst. Appl.*, vol. 47, pp. 95–105, Apr. 2016.

[15] H. E. Lambert, "Fault trees for locating sensors in process systems," *Chem. Eng. Progr.*, vol. 73, no. 8, pp. 81–85, 1977.
[16] H. Park and A. Haghani, "Optimal number and location of Bluetooth sensors considering stochastic travel time prediction," *Transp. Res. C, Emerg. Technol.*, vol. 55, pp. 203–216, Jun. 2015.
[17] P. Sen, K. Sen, and U. M. Diwekar, "A multi-objective optimization approach to optimal sensor location problem in IGCC power plants," *Appl. Energy*, vol. 181, pp. 527–539, Nov. 2016.
[18] L. Vincenzi and L. Simonini, "Influence of model errors in optimal sensor placement," *J. Sound. Vibrat.*, vol. 389, no. 17, pp. 119–133, Feb. 2017.
[19] H. Zhang, R. Ayoub, and S. Sundaram, "Sensor selection for Kalman filtering of linear dynamical systems: Complexity, limitations and greedy algorithms," *Automatica*, vol. 78, pp. 202–210, Apr. 2017.
[20] J. D. Schaffer, "Multiple objective optimization with vector evaluated genetic algorithms," in *Proc. 1st Int. Conf. Genetic Algorithms Their Appl.*, 1985, pp. 93–100.
[21] N. Hu, P. Zhou, and J. Yang, "Comparison and combination of NLPQL and MOGA algorithms for a marine medium-speed diesel engine optimisation," *Energy Convers. Manage.*, vol. 133, pp. 138–152, Feb. 2017.
[22] J. Horn, N. Nafpliotis, and D. E. Goldberg, "A niched Pareto genetic algorithm for multiobjective optimization," in *Proc. IEEE World Congr. Comput. Intell.*, Jun. 1994, pp. 82–87.
[23] N. Alikar, S. M. Mousavi, R. A. R. Ghazilla, M. Tavana, and E. U. Olugu, "Application of the NSGA-II algorithm to a multi-period inventory-redundancy allocation problem in a series-parallel system," *Rel. Eng. Syst. Saf.*, vol. 160, pp. 1–10, Apr. 2017.
[24] A. Attar, S. Raissi, and K. Khalili-Damghani, "A simulation-based optimization approach for free distributed repairable multi-state availability-redundancy allocation problems," *Rel. Eng. Syst. Saf.*, vol. 157, pp. 177–191, Jan. 2017.
[25] X. Hong, S. Chen, and V. M. Becerra, "Sparse density estimator with tunable kernels," *Neurocomputing*, vol. 173, pp. 1976–1982, Jan. 2016.
[26] A. Youssef, C. Delpha, and D. Diallo, "An optimal fault detection threshold for early detection using Kullback–Leibler divergence for unknown distribution data," *Signal Process.*, vol. 120, pp. 266–279, Mar. 2016.
[27] Y. Zhang and C. Ma, "Fault diagnosis of nonlinear processes using multiscale KPCA and multiscale KPLS," *Chem. Eng. Sci.*, vol. 66, no. 1, pp. 64–72, 2011.
[28] Y. Fu, U. Kruger, Z. Li, L. Xie, J. Thompson, D. Rooney, J. Hahn, and H. Yang, "Cross-validatory framework for optimal parameter estimation of KPCA and KPLS models," *Chemometrics Intell. Lab. Syst.*, vol. 167, pp. 196–207, Aug. 2017.
[29] M. A. Abido, "Multiobjective evolutionary algorithms for electric power dispatch problem," *IEEE Trans. Evol. Comput.*, vol. 10, no. 3, pp. 315–329, Jun. 2006.

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