IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 12 April 2024, accepted 18 April 2024, date of publication 24 April 2024, date of current version 2 May 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3392905

RESEARCH ARTICLE

A Novel Reduced-Order Analytical Fault Diagnosis Model for Power Grid

ZHUONAN LIN[1], YONGXING WANG[2], (Member, IEEE), HAOQIAN XU[3], AND FANRONG WEI[4]

[1]Leicester International Institute, Dalian University of Technology, Panjin 124221, China
[2]School of Electrical Engineering, Dalian University of Technology, Dalian 116023, China
[3]College of Electrical Engineering and New Energy, China Three Gorges University, Yichang 443002, China
[4]School of Electrical and Electronic Engineering, Huazhong University of Science and Technology, Wuhan 430074, China

Corresponding author: Fanrong Wei (610300307@qq.com)

This work was supported by the National Natural Science Foundation of China under Grant 52107095.

ABSTRACT Power grid fault diagnosis methods based on analytical models possess advantages such as logical rigor, strong interpretability, and high applicability. However, the existing design of their objective functions is presented as a 0-1 integer nonlinear programming model, making it difficult to approximate the optimal solution. To address this issue, this paper proposes an improvement to the expression of the second backup protection expectation involved in the diagnostic model. Thus, the order of the objective function is successfully reduced, transforming the original 0-1 integer nonlinear programming model into a constrained 0-1 integer linear programming model, which can be efficiently solved by typical commercial solvers based on a linear integer programming framework. Numerical results demonstrate that the solution time of the proposed linearized model is lower than that of existing nonlinear programming models, and the diagnostic accuracy of the proposed model is higher than that of other state-of-the-art methods.

INDEX TERMS Analytical models, circuit breakers, fault diagnosis, heuristic algorithms, integer linear programming, linearization techniques, optimization methods, power grids, power system protection, problem solving.

I. INTRODUCTION

When a fault event occurs in a power grid, rapid and accurate fault diagnosis is important for efficient fault processing and ensuring reliable operation of the power grid. Generally, the existing methods for power grid fault diagnosis include expert systems, artificial neural networks, Petri nets, and analytical models [1], [2], [3], [4], [5]. The advantages and disadvantages of these methods are as follows.

Initially, expert systems were introduced to establish a fault diagnosis model. These fault diagnosis methods do not require a large amount of power grid data, and the obtained solutions have strong interpretability [6]. However, updating and maintaining the knowledge base of expert systems is quite difficult when the power grid topology or parameters change to some extent.

The associate editor coordinating the review of this manuscript and approving it for publication was Gerard-Andre Capolino.

Compared with fault diagnosis methods based on expert systems, those based on artificial neural networks are more adaptable. For example, Ref. [7] quantified and classified alarm information using a random forest classification algorithm. Ref. [8] proposed a graph-encoding-based method to provide a unified data representation for deep learning models. Ref. [9] converted collected data into polar coordinates, and the processed data were subsequently used as the input of a convolutional neural network. This greatly improved the diagnostic accuracy and efficiency. In addition, Ref. [10] proposed a fault diagnosis method based on deep reinforcement learning for informational alarm text. This paper sought to determine the faulty circuit without relying on the network topology; rather, the topology relationships and action logic are learned. Simulation tests demonstrate that using this method, correct fault diagnosis results can be achieved, and information about the faulty circuit breaker involved in the event can be obtained. The integrated fault diagnosis system proposed in Ref. [11] uses accident-level information, warning-level information and fault recording documents and outputs a complete diagnosis and tracking report. This system can screen out incorrectly operating protections and circuit breakers and judge the loss of accident-level information. Additionally, it can determine the reasons for incorrect protections and circuit breakers while considering partially missing warning-level information. Ref. [12] proposed a distributed fast fault diagnosis method for multimachine power systems based on deterministic deep learning theory, which can quickly recall the dynamic memory of transient faults and make quick fault diagnosis decisions. Ref. [13] proposed a transmission line fault diagnosis method based on an improved multiple SVM model that can overcome the limitations of small samples and generalization accuracy. Moreover, Refs. [14] and [15] adopted a methodology for integrating multiple artificial neural networks or combining artificial neural networks with other algorithms, such as the elgamal encryption algorithm, to further improve the accuracy of the fault analysis results.

Despite its advantages with regard to adaptability, fault diagnosis based on artificial neural networks requires a large amount of diverse fault data, particularly representative data, for training to generate a feasible diagnostic model with a satisfactory accuracy rate. However, the actual fault data of power grids are very limited; moreover, these data must be supplemented with a large number of simulations, which weakens the generalizability of such models.

In addition to fault diagnosis based on artificial neural networks, Petri nets use graph and matrix operations to analyze power system faults. Ref. [5] proposed a fault diagnosis model based on temporal constrained fuzzy Petri nets (TCFPNs), which introduces the true value and temporal contribution of alarms into the graphical model of the TCFPN to obtain the fault probability and time constraints for each candidate segment. Ref. [16] proposed a power grid fault diagnosis method based on an intuitionistic fuzzy inhibitor arc Petri net (IFIAPN) and the error back-propagation algorithm. Based on the network topology analysis and protection configuration rules, the inhibitor arc tuple is introduced into the model structure of the IFIAPN to reduce the fuzziness of protection and circuit breaker actions. Then, the weight parameters in the model are trained using the back-propagation neural network algorithm to enhance the objectivity of the parameters. Ref. [17] proposed a fault diagnosis method based on intuitive fuzzy sets and incidence matrices to address the uncertainty of alarm information as well as the topology changes of a power system. Ref. [18] proposed a fault diagnosis method based on a fuzzy decision tree (FDT), which introduces a fuzzy rule base to a conventional decision tree by incorporating multiclass decisions at the terminal nodes with a certain probability for each participating class. Moreover, in Ref. [19], a novel fault diagnosis method based on differential current was presented to address complex faults and uncertain factors such as maloperation, missed operations and missing messages. This enables rapid, accurate, flexible and portable identification of faults.

It is important to note that fault diagnosis based on Petri nets is more suitable for smaller systems. As the scale of the power grid to be diagnosed becomes larger, construction of the Petri net becomes complex and even infeasible due to the problem of combinatorial explosion.

Compared with the aforementioned models, fault diagnosis based on an analytical model has advantages such as a rigorous theoretical foundation, simple logic, strong interpretability of the obtained results, and greater suitability for practical use [20], [21]. The key to this approach lies in establishing a reasonable fault diagnosis model, and an optimization algorithm is used to ensure the rapid and accurate discovery of the optimal solution [22], [23], [24]. Recently, models that use multisource information and incorporate data uncertainties have been studied. Recent progress was reported in [25] and [26]. However, because the secondary backup protection expectation function is designed with multiple component state multiplications, the fault diagnosis problem becomes an integer nonlinear programming problem. In this case, conventional linear programming methods cannot be used [27]. Instead, heuristic intelligent algorithms such as genetic algorithms and particle swarm optimization are employed. To further improve the global optimization ability of the algorithm and improve the accuracy of fault diagnosis for power grid faults, the genetic algorithm taboo search (GATS) method was introduced in Refs. [28] and [29], and a fault localization method was proposed that combines an improved matrix algorithm based on multisource information and a GATS method to address the limitations of existing fault localization methods in active distribution networks, such as high computational cost, low accuracy, and low tolerance performance.

However, the search performance of these algorithms depends strongly on the initial settings, and the obtained solutions are prone to becoming trapped in local optima, making it challenging to achieve satisfactory solution speed.

The above problem can be solved naturally if the diagnosis model can be linearized. In the field of fault diagnosis for distribution networks, great progress has already been made in this area [30], [31]. However, the methodology of the above literature cannot be directly applied in the design of fault diagnosis models for main power grids. These fault diagnosis methods use no discrete information regarding protection or circuit breakers; instead, they rely on detailed information on branch currents obtained by the feeder terminal unit (FTU) or even new fault detection devices. The information on whether the fault current flows through a certain branch is necessary, and is used together with the information on the direction of fault currents. Based on this type of fault diagnosis method, it is relatively easy to establish a diagnosis model based on linear integer programming. However, classic fault diagnosis models for transmission grids rely more on the inherent coupling relationship between protection and circuit breaker information. Therefore, because the initially established power grid fault diagnosis model takes complicated faults into account and must consider more complete protection coordination logic, it inevitably exhibits nonlinear characteristics.

In view of the aforementioned problems, on the basis of the classical fault diagnosis model from Ref. [21], an improved analytical fault diagnosis model for power grids is proposed. The main contributions of this paper can be summarized as follows.

First, the mechanism that gives rise to a relatively high false solution rate in the case of complicated faults accompanied by maloperation or failure to trip for the analytic model-based methods is presented. By contrast, the existing methods have not yet conducted corresponding theoretical analyses; thus, they can only improve algorithms empirically. For instance, Refs. [23] and [25] modify the objective function according to field experience to enhance the adaptivity to complicated faults. Moreover, Ref. [26] assumed that the high false solution rate was mainly due to the insufficient performance of the heuristic solving algorithms adopted and introduced an improved solving algorithm to obtain better results.

Second, a completely new analytical diagnosis model for power grids is obtained by changing the expression of the second backup protection expectation from an equality constraint to an inequality constraint, transforming the original 0-1 integer nonlinear programming model into a constrained 0-1 integer linear programming model that can be directly solved using classical commercial solving tools. By contrast, the existing analytical model-based approaches [20], [21], [22], [23], [24], [25], [26] adopt high-order analytical models, which can be solved only by heuristic algorithms, resulting in decreased diagnostic accuracy.

Third, a detailed evaluation of the model's fault tolerance is conducted, and the upper limit of fault tolerance is revealed. By comparison, the fault tolerance of analytical models has not been thoroughly analyzed in the existing works, making it difficult to determine under what circumstances the diagnostic accuracy will decrease.

Extensive comparative analyses of numerous cases demonstrate that the proposed method is superior to traditional approaches in terms of solution speed and accuracy and that it exhibits strong universality.

II. BENCHMARK MODEL AND ITS IMPROVEMENT OF POWER GRID FAULT DIAGNOSIS

The objective of the proposed classic analytical fault diagnosis model for power grids is to reveal the lurking information of the fault components contained in the action signals of the protection and circuit breaker, and its objective function is generally designed as follows:

$$\min E(X) = \sum \left| r_i - r_i^* \right| + \sum \left| C_m - C_m^* \right| \tag{1}$$

where $X = (S, r, C)$ represents the state vector consisting of the component state, protection state, and circuit breaker state; $S_\mathrm{i}$represents the state of the ith component, of which

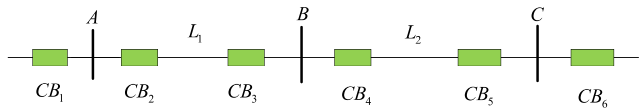

FIGURE 1. Configuration of a sample transmission system for depicting the analytical fault diagnosis mode.

0 represents normal and 1 represents false; C_m represents the state of the mth circuit breaker, for which 0 means closed and 1 represents open; r_i represents the state of the ith protection, for which 0 represents untripped and 1 represents tripped; C_m^*represents the expected state of the mth circuit breaker, for which 0 represents the expectation to be closed and 1 represents the expectation to be open; r_i^* represents the expected state of the nth protection, for which 1 represents the expectation to be tripped and 0 represents the expectation to not trip; and $C_m^*$and r_i^*must be calculated based on the action logic of the protections.

The system shown in Fig. 1 is taken as an example to explain the design of protection expectations and circuit breaker expectations and to analyze the drawbacks of the present schemes. In the original model, the expected values of protection status can be represented using the substation status and corresponding circuit breaker states, as depicted in Fig. 1.

Taking the main protection r_{L1Am}, first backup protection r_{L1Ap}, and second backup protection r_{L1As} near bus A in the system shown in Fig. 1 as an example, the corresponding expected values for protection actions are shown in (2):

$$\begin{cases} r_{L1Am}^* = S_{L1} \\ r_{L1Ap}^* = S_{L1}(1 - L_{1Am}) \\ r_{L1As}^* = 1 - [1 - S_B(1 - C_3)][1 - S_{L2}(1 - C_3)(1 - C_4)] \\ C_2^* = \max\{S_{L1} r_{L1Am}, S_{L1}(1 - r_{L1Am}) r_{L1Ap}, S_A A_m, \\ \qquad r_{L1As}^* r_{L1As}\} \end{cases} \tag{2}$$

where r_{L1Am}^*, r_{L1Ap}^*, r_{L1As}^* represent the expected values of protective devices, 1 represents the expectation of being tripped, and 0 represents the expectation of not being tripped. r_{L1Am}, r_{L1Ap}, and r_{L1As} are the actual action values. S represents the status of components, with subscripts corresponding to specific components. A faulted status occurs when S is 1, whereas a normal status occurs when S is 0. C represents the actual status of the circuit breakers, where 1 represents an open state and 0 represents a closed state.

The fault diagnosis model formed by (1) and (2) can be regarded as an integer nonlinear programming problem with S as the unknown state variable. From (2), it is evident that the expectation of the second backup protection for line *L1* contains the product of two state variables, S_B and S_{L2}. Substituting these variables into (1), it is found that the fault diagnosis problem is actually a high-order 0-1 integer nonlinear programming problem. When the system structure becomes more complex, the problem-solving process becomes more difficult. For example, if there are double-circuit transmission lines between buses B and C in Fig. 1, three variables will be multiplied, increasing the order of the objective function to three. Considering the increasing prevalence of multicircuit lines on the same tower, situations with four or even eight circuits on the same tower may arise, leading to even higher-order objective functions.

The above integer programming model exhibits significant nonlinear and nonconvex characteristics, making it a typical NP-hard problem. As a result, it is difficult to obtain optimality conditions directly, and theoretically, only exhaustive search methods can be used to find the optimal solution. However, an exhaustive search is an algorithm with exponential complexity, which makes it impractical for engineering applications. Instead, one can resort to relaxation by converting the problem to a continuous problem and then rounding the continuous solutions or introducing heuristic algorithms to find approximate solutions. Nevertheless, the rounding operation alters the original nature of the problem, and the solution obtained after rounding may not be feasible. Even if the original constraints are satisfied, the quality of the solution may be poor. Consequently, for such problems, both the theoretical and engineering communities often turn to heuristic methods such as genetic algorithms, simulated annealing, and particle swarm optimization. While these algorithms demonstrate strong adaptability to optimization problems, they are prone to becoming stuck in local optima when solving nonlinear and nonconvex problems. Additionally, the obtained solutions are highly sensitive to the initial values, making it challenging to guarantee the superiority of the results and the solution time.

The above-discussed fault diagnosis model based on nonlinear integer programming is actually a diagnostic model based on the optimization technology. This approach creatively transforms the power grid fault diagnosis problem into a 0-1 integer programming problem for finding extrema; thus, the problem has a rigorous mathematical foundation and can be effectively implemented using conventional algorithms. In theory, it can cover all diagnostic rules of expert systems, regardless of the complexity of the topology of the system to be diagnosed. The true faulty components can be identified based on flawed basic data through meticulous logical design as long as the binary signals of the corresponding circuit breaker and protection can be obtained. This type of model can obtain appropriate results for both a single fault and a complicated fault, regardless of whether the information is complete or partially missing. In this sense, it is a practical model with high theoretical value.

However, as mentioned earlier, such models also have certain limitations. For example, in some cases, the area to be diagnosed may be relatively broad, for example due to maloperation and failure-to-trip protection. In this case, the diagnostic model constructed dynamically using the obtained protection and circuit breaker signals may be relatively high-dimensional. Therefore, the number of variables to be optimized will increase nonlinearly, causing the search space to rapidly expand. The computational workload of each iteration will increase exponentially. Under some conditions, the

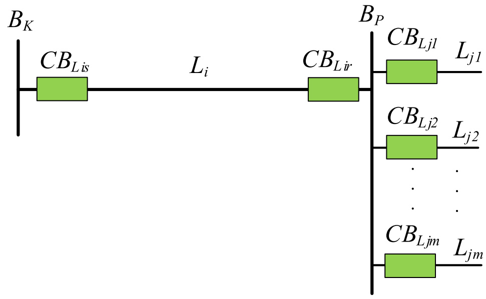

FIGURE 2. Generalized line and bus model corresponding to the framework diagram.

solution time cannot meet the on-site application requirements. As a compromise, a feasible solution can be obtained by forcibly interrupting the search process through setting a threshold. However, this solution may be far from the optimal solution. In addition, missing or multiple solutions cannot be avoided. In view of this, the order of this type of thoroughly principled analytical model of fault diagnosis should be reduced by an equivalent transformation of the objective function. Thus, the drawbacks of directly using heuristic algorithms can be avoided, and the probability of obtaining satisfactory solutions can be increased while maintaining the superiority of such models.

Therefore, the key to solving the above problem is to transform the original problem from a high-order 0-1 integer nonlinear programming problem to a 0-1 integer linear programming problem. If this is achieved, specific algorithms for solving the above problem can be used, offering a chance to obtain an approximate optimal solution that closely approximates the true solution.

By analyzing the expression for the expectation of the second backup protection status in (2), it is possible to reformulate it from an equation containing state multiplications into inequality constraints, the expression of main protection, first backup protection and breaks are unchanged, as shown in (3):

$$\begin{cases} r^*_{L1As} \geq S_B(1-C_3) \\ r^*_{L1As} \geq S_{L2}(1-C_3)(1-C_4) \\ r^*_{L1As} \leq S_B(1-C_3)\,|S_{L2}(1-C_3)(1-C_4) \\ C^*_2 = \max\{S_{L1}r_{L1Am}, S_{L1}(1-r_{L1Am})r_{L1Ap}, S_A A_m, \\ \qquad r^*_{L1As}r_{L1As}\} \end{cases} \tag{3}$$

Successful linearization of the model can be achieved through the transformation described above. In this transformation, the original optimization variables $\{S_{\mathrm{i}}\}$ are expanded to include $\{S_i, r_i\}$ (where r_i represents the expectation of the second backup protection status). This expansion increases the search space to some extent, but the original 0-1 integer nonlinear programming problem has been successfully reduced to a constrained 0-1 integer linear programming problem.

After adopting the above improvements, the models described in (3) and (2) are logically identical. The difference

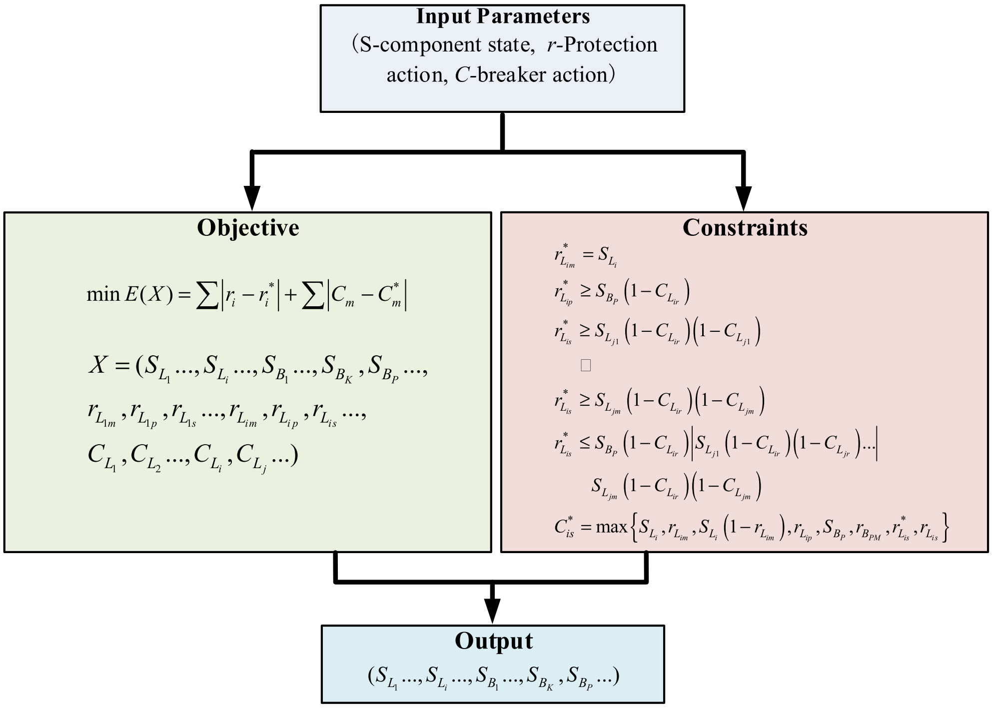

FIGURE 3. Framework diagram of the fault diagnosis model.

is that the model shown in (3) transforms the direct optimization of state S into the first optimization of protection r^* and then determines the required component state S. Through equivalent substitution on the upper surface, it can be seen that in no case the desired quantity r^* is multiplied when optimizing r^*, realizing the linearization of the model and facilitating its solution.

Various advanced algorithms based on integer linear programming frameworks, such as branch and bound methods and cutting plane methods, can be used to solve integer linear programming problems. These algorithms can easily provide approximate optimal solutions for any complex scenario.

Without loss of generality, as shown in Fig. 2, we select a transmission line from the power grid and name it as L_i, the busbars corresponding to Line L_i as B_K and B_P, and the circuit breakers corresponding to Line L_i as $CB_{L_{is}}$and $CB_{L_{ir}}$. Then we assume there are m transmission lines other than this line also connected to busbar B_P, and denote them as $L_{j1},\ldots,$ L_{jm}, and the corresponding breakers as $CB_{Lj1},\ldots, CB_{Ljm}$.

Then we present the framework diagram of the fault diagnosis model in Fig. 3. In this figure, $S_{L_i}, S_{L_{j1}},\ldots,$ $S_{L_{jm}}\ldots$ denote the status of the transmission lines; $C_{L_{is}}$, $C_{L_{ir}}$, $C_{L_{j1}},\ldots, C_{L_{jm}}$ denote the status of the circuit breakers, and the superscript with * indicates the corresponding expected state. Taking the sending end protection of transmission line L_i as an example, $r_{L_{im}}$denotes the status of the first main protection, $r_{L_{ip}}$ denotes the first backup protection, and $r_{L_{is}}$ denotes the second backup protection. Other protection status and their expectation will be defined in the similar way. With the input parameters, the objective function, as well as the constraints, we could solve the fault diagnosis model and obtain the status of all the transmission lines and busbar thus to identify the faulted components.

III. DIAGNOSIS PROCEDURE AND MODEL SOLVING

In the above section, this paper establishes an analytical model for power grid fault diagnosis based on 0-1 integer linear programming, which greatly increases the probability of obtaining the optimal or approximate optimal solution. Nevertheless, the solution of integer programming models is still NP-hard. Fortunately, the commercial optimization solver GUROBI combines heuristic algorithms and linear programming algorithms well and can be applied to efficiently solve the model in this paper.

Therefore, after establishing the model, it was programmed in MATLAB and the middleware Yamip was used to call the integrated linear programming algorithms in GUROBI directly for solving. The complete procedure of fault diagnosis is illustrated in Fig. 4.

First, the diagnostic model collects the necessary alarm information from the protection and information systems, including the actions of the involved protections and circuit breakers. The collected information is substituted into the diagnosis model to perform the optimization procedure. In this stage, GUROBI is used to locate the faulted components. After all component states are available, the results are output to the operating staff for reference. The framework used by GUROBI to solve MIPs includes branches and cuts, but heuristic algorithms are used at each node when exploring branch and cut trees to quickly obtain high-quality integer feasible solutions and accelerate the convergence of the update gap of the upper bound. Moreover, the cutting

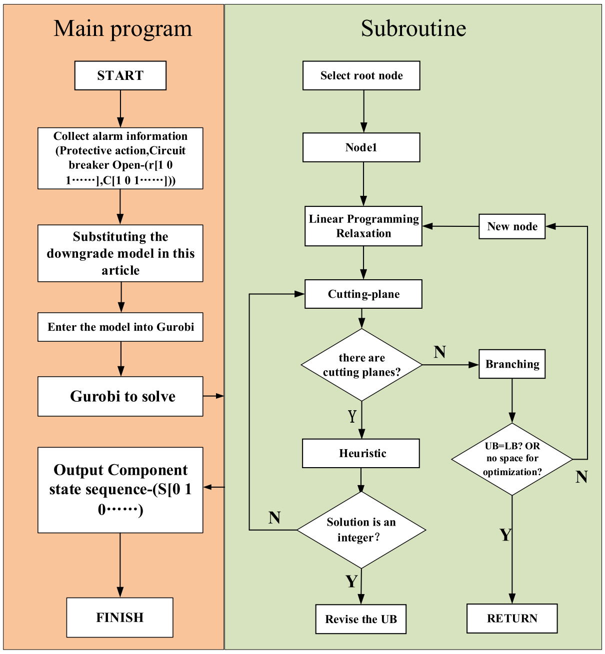

FIGURE 4. Fault diagnosis procedure based on the linear programming solving framework.

plane algorithm is also used on each node to generate a cutting plane, tighten the model, approximate the convex hull of the feasible region of the node, and tighten the lower bound.

The simulation results shown in the next section verify that GUROBI fully meets the solving requirements of the power grid fault diagnosis analytical model based on 0-1 integer linear programming.

IV. TOLERANCE ANALYSIS OF INFORMATION DISTORTION

After a fault occurs, the secondary station of the protection information system collects and uploads the action information of the protections and circuit breakers to the main station. However, missing information or distortion during upload is inevitable. Because this situation is extremely unfavorable for fault diagnosis, it is generally required that the fault diagnosis system has a certain degree of tolerance for information distortion. The fault tolerance of the model is discussed below using the simple power grid shown in Fig. 1.

For instance, assume that a fault occurs on line L_2 In this case, protections r_{L2Bm} and r_{L2Bp} fail to trip, and protections r_{L1As}, r_{L2Cm} trip, and circuit breakers C_2, and C_5 operate. Distortion occurs during information upload, resulting in the information collected by the main station being $r_{L1As} = 1$, $C_2 = 1$, $C_5 = 1$, $r_{L2Cm} = 0$. The constraint conditions about $r^*_{L1AS}$are derived from (3), as shown in (4):

$$\begin{cases} r^*_{L1As} \geq S_B \\ r^*_{L1As} \geq S_{L2} \\ r^*_{L1As} \leq S_B \,|S_{L2} \end{cases} \tag{4}$$

It can be seen from (1) that, to minimize the objective function, we should let $r^*_{L1As} = 1$, $C^*_2 = 1$, $C^*_5 = 1$. Combining the above results with (4), we know that at least one of S_{L2} and S_B is 1. If $S_{L2} = 1$, the value of the objective function will be higher than that in other cases; thus, the final diagnosis result should be $S_B = 1$ and $S_{L2} = 0$.

Then, assume that there is a fault on line L_2, protections r_{L2Bm} and r_{L2Bp} fail to trip, protections r_{L1As} and r_{L2Cm} trip, and circuit breakers C_2 and C_5 operate. Distortion occurs during information upload, and the information collected by the main station is $r_{L1As} = 0$, $C_2 = 1$, $C_5 = 1$, $r_{L2Cm} = 0$. The constraint conditions about $L^*_{1AS}$are derived from (3), as shown in (4). In this case, $C^*_2 and C^*_5$ is

$$\begin{cases} C^*_2 = \max\{0, 0, 0, 0\} \\ C^*_5 = \max\{0, 0, 0, 0\} \end{cases} \tag{5}$$

To minimize the objective function, $r^*_{L1As} = 0$, $S_{L2} = 0$, indicating a diagnosis result of no fault, and the circuit breakers are tripped incorrectly. Clearly, this is a misjudgment.

As seen from the above case analysis, the proposed method still achieves satisfactory performance even in the presence of missing information, distortion or inappropriate protection actions. However, if an extreme scenario occurs, for instance, all protections associated with the faulty component fail to trip or all of the uploaded action information of the protections associated with the fault is 0 due to information distortion, the method described in this paper cannot determine the faulty component. Nevertheless, for any fault diagnosis method, the diagnostic performance may be relatively poor in extreme situations in which all kernel information is missing or protection operations are incorrect. However, the probability of these extreme situations occurring in reality is extremely small. In this sense, the fault tolerance capability of the method proposed in this paper can meet practical needs.

V. CASE STUDY

To demonstrate the advantage of the proposed method over the purely heuristic algorithm-based methods, the genetic algorithm, simulated annealing algorithm, and the particle swarm optimization algorithm are used as the solving algorithms for the diagnosis model proposed in Ref. [21]. Among the three algorithms mentioned above, the algorithm with the best diagnostic results and lowest diagnostic time was selected and compared with the results from GUROBI to verify the effectiveness of the algorithm. For all simulation tests, the CPU used in the simulation is an Intel-i5-1135G7 CPU.

First, assume that faults occur on L_1, L_2, L_7 and L_8, as shown in Fig. 5, and that the main protections and circuit breakers of the corresponding lines operate correctly. In this case, the most suitable initial population size and iteration number for the genetic algorithm, simulated annealing algorithm, and particle swarm optimization algorithm are determined by changing the initial population size and iteration number. Furthermore, the time consumption and accuracy of the results for diagnosing complex faults for the genetic, simulated annealing, and particle

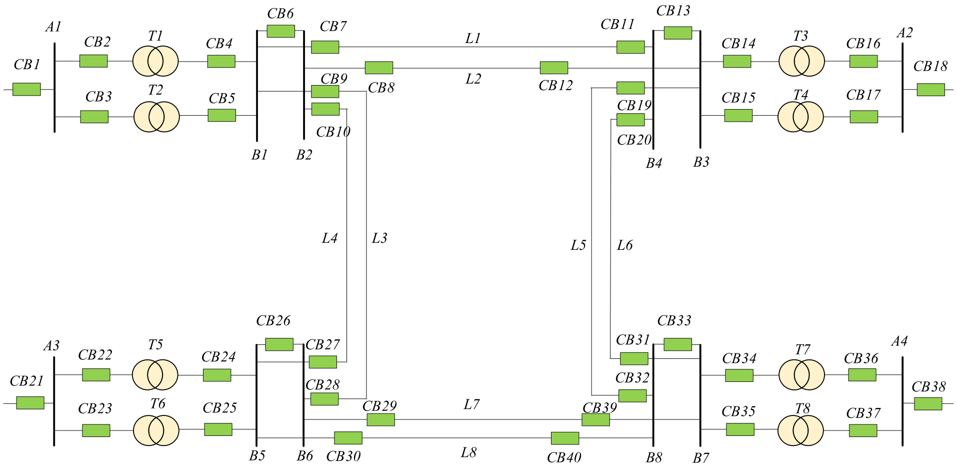

FIGURE 5. Benchmark transmission system involving multiple lines, busbars and transformers for fault diagnosis.

TABLE 1. Solution time and diagnosis accuracy of genetic algorithms with different initial population sizes and iteration times.

Iteration time/Population	Diagnosis Results	Evaluation	Time (s)
10/20	L_8	WRONG	13.85
10/100	L_1, L_7, L_8	WRONG	109.7
10/150	L_1, L_7, L_8	WRONG	246
20/20	L_2, L_8	WRONG	63
20/50	L_1, L_2, L_7, L_8	CORRECT	157
20/60	L_1, L_2, L_7, L_8	CORRECT	285.8
20/100	L_1, L_2, L_7, L_8	CORRECT	467.7
10/50	L_1, L_2, L_7, B_1	CORRECT	115
30/50	L_1, L_2, L_7, L_8	CORRECT	181
10/60	L_1, L_2, L_7, L_8	CORRECT	186

TABLE 2. Solution time and diagnosis accuracy of simulated annealing algorithms with different iterations.

Iteration time	Diagnosis Results	Evaluation	Time (s)
100	A_1,A_2, L_1	WRONG	29
200	A_1,A_2, L_1,B_1	WRONG	59.5
1000	B_1,T_1,L_1,L_8	WRONG	176.3
10000	L_1,L_2, L_7, L_8	CORRECT	632.1

TABLE 3. Solution time and diagnosis accuracy of particle swarm algorithms with different particle swarm sizes and numbers of iterations.

Iteration time/Population	Diagnosis Results	Evaluation	Time (s)
20/20	L_1, L_2, L_8, A_1	WRONG	121
20/50	L_1, L_2, L_7, L_8	CORRECT	336.5
20/40	L_1, L_2, L_7, L_8, A_4	WRONG	387
50/20	L_1, L_2, L_7, L_8	CORRECT	345
40/20	L_1, L_2, L_7, L_8	CORRECT	320
30/20	L_1, L_2, L_3, L_7, L_8	WRONG	259

swarm optimization algorithms are used as indices to select the optimal algorithm for comparison with the proposed method, as shown in Tables 1∼3. The results obtained by genetic algorithm, simulated annealing, and particle-swarm optimization are influenced by the initial population, number of iterations, and other factors (such as mutation and crossover factors in genetic algorithms, inertia weights, individual learning factors, and population learning factors in particle-swarm optimization algorithms). Therefore, each diagnostic result may be inconsistent, or multiple solutions may exist. Note that the solution times given for the above algorithms are the averages of multiple experimental results.

According to TABLE 1, the consistency of the solutions can be guaranteed when the number of iterations of the genetic algorithm is 20 and the initial population is 50. Although increasing the population size can also yield correct results, the solving time greatly increases. By contrast, when the initial population is set to 50 and the number of iterations is reduced to 10, the solving effect of the genetic algorithm is poor. Setting the number of iterations to 10 and increasing the initial population to 60 to repeat the tests, the solution time is also longer, although correct results can also be obtained. Therefore, the number of iterations and the initial population of the genetic algorithm are determined to be 20 and 50, respectively.

Table 2 shows that the performance of the simulated annealing algorithm is relatively unsatisfactory. The correct results are unavailable until the number of iterations reaches 10,000, at which point the convergence is quite slow.

Comparison of the results presented in TABLES 1 and 3 shows that compared to the genetic algorithm, the particle swarm optimization algorithm requires more time to achieve the correct results.

TABLEs 1∼ 3 show that the genetic algorithm has the best performance among the existing heuristic algorithms considering various indices. Therefore, this paper ultimately selects the model proposed in Ref. [21] using a genetic algorithm (with 20 iterations and 50 initial populations) as the solver for comparative analysis.

Simulations and comparative analyses were conducted on the system depicted in Fig. 5. The tests are designed with a large number of representative simple fault scenarios and complicated fault scenarios with inappropriate protection

TABLE 4. Comparison of the results of the proposed model and those of the model in Ref. [21].

Case No.	Action Signal	Result for Ref. Model	Time (s)	Result from Proposed Model	Time(s)
1	$r_{\mathrm{B}1m}$,$r_{\mathrm{L}2Rs}$,$r_{\mathrm{L}4Rs}$ Trip C_4,C_5, C_7,C_9,C_{12},C_{27} Open	B_1	106	B_1	0.5
2	r_{T5s},r_{T6s} Trip C_{22},C_{23},C_{24},C_{25} Open	A_3	126	A_3	0.53
3	$r_{\mathrm{L}1m}$,$r_{\mathrm{L}1Sp}$,$r_{\mathrm{L}1Rm}$ Trip C_4,C_5,C_6,C_7,C_9,C_{11} Open	B_1 and L_1	183	B_1 and L_1	0.49
4	$r_{\mathrm{L}1Sm}$,$r_{\mathrm{L}1Sp}$,$r_{\mathrm{L}1Rp}$ Trip C_7,C_{11}Open	1.L_1 2.No-fualt	137	L_1	0.49
5	$r_{\mathrm{B}1m}$,$r_{\mathrm{B}2m}$,$r_{\mathrm{L}1Sm}$, $r_{\mathrm{L}1Rp}$,$r_{\mathrm{L}2Sp}$,$r_{\mathrm{L}2Sm}$ Trip C_4,C_5,C_6,C_7,C_9,C_{10}, C_{11} Open	B_1,L_1,B_2, L_2	206	B_1,L_1,B_2,L_2	0.46
6	$r_{\mathrm{T}3P}$,$r_{\mathrm{L}7Sp}$,$r_{\mathrm{L}7Rp}$Trip C_{14},C_{16},C_{29},C_{39} Open	1.T_3,L_7 2.T_3 3.L_7 4.No-fault	158	T_3,L_7	0.51
7	$r_{\mathrm{T}7m}$,$r_{\mathrm{T}8p}$,$r_{\mathrm{B}7m}$,$r_{\mathrm{B}8m}$, $r_{\mathrm{L}5Sm}$,$r_{\mathrm{L}5Rp}$,$r_{\mathrm{L}6Ss}$, $r_{\mathrm{L}7Sp}$,$r_{\mathrm{L}7Rm}$,$r_{\mathrm{L}8Ss}$Trip C_{19},C_{20},C_{29},C_{30},C_{32}, C_{33},C_{34},C_{35},C_{36},C_{37}, C_{39}Open	1.T_8,T_7 2.L_5,L_7, B_8,B_7 3.T_7,L_5,L_7,B_8,B_7	173	T_8,T_7,L_5,L_7,B_8,B_7	0.6
8	$r_{\mathrm{L}1Sm}$,$r_{\mathrm{L}1Rp}$,$r_{\mathrm{L}2Sp}$, $r_{\mathrm{L}2Rp}$,$r_{\mathrm{L}7Rm}$,$r_{\mathrm{L}7Sp}$, $r_{\mathrm{L}8Rm}$,$r_{\mathrm{L}8Sm}$Trip C_7,C_8,C_{11},C_{12},C_{29},C_{30} ,C_{39},C_{40} Open	1.L_1,L_2,L_7,L_8 2.L_1,L_8,L_7	143	L_1,L_2,L_7,L_8	0.53
9	r_{L1Sm},r_{L1Sp},r_{L1Rp}, r_{L1Rs},r_{T1s},r_{T2s},r_{L2Ss}, r_{L3Rs},r_{L4Ss}Trip C_4,C_6,C_7,C_{11},C_8,C_9, C_{10}Open	1.L_1,A_1 2.L_1,B_2	221	L_1,B_1,B_2	0.71

operations. Diagnostic results and diagnostic times are generated based on the model proposed in this paper and the model from Ref. [21]. A comparative analysis is then performed.

It should be noted that the model from Ref. [21] was simplified to accommodate heuristic algorithm solutions, which may introduce errors. By contrast, the model proposed in this paper can preserve the accuracy of the original model because it performs only an equivalent transformation on the original model, as demonstrated in (1) and (2). Due to space limitations, only a portion of the typical results from specific test cases are presented in TABLE 4. The table includes the diagnostic results and diagnostic times obtained using both models for various fault scenarios. Some of the test results (examples 4 to 9) for complex test cases involving multiple faults and numerous inappropriate protection actions are shown in TABLE 4.

Case 4: Line L_1 encounters a fault, and the main protection at the sending end of line L_1 trips correctly. However, the first backup protection maloperates, and the main protection "$r_{\mathrm{L}_{1Rm}}$" at the receiving end of line L_1 fails to trip, while the first backup protection can trip correctly. The circuit breakers C_7 and C_{11} are operated correctly. In this scenario, the model from Ref. [21] produces an erroneous diagnosis, indicating no fault, while the model proposed in this paper successfully provides the correct diagnosis result.

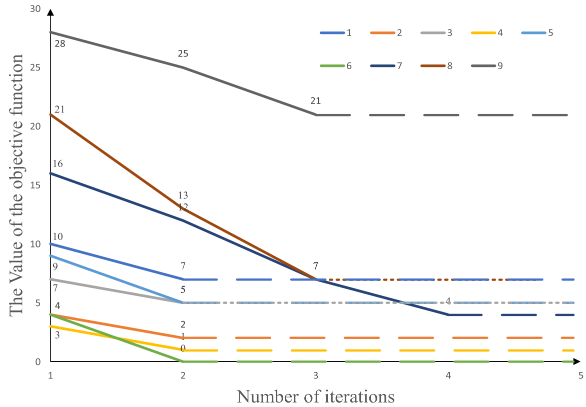

FIGURE 6. Convergence curves of different fault cases with the advanced iterative algorithm embedded in GUROBI.

Case 9: Buses B_1 and B_2, as well as line L_1, encounter faults. The bus protections "$r_{\mathrm{B}_{1m}}$" and "$r_{\mathrm{B}_{2m}}$" fail to operate, while the second backup protections on adjacent lines, namely, "$r_{\mathrm{L}_{1Rs}}$", "$r_{\mathrm{L}_{3Rs}}$", "$r_{\mathrm{T}_{1s}}$", "$r_{\mathrm{T}_{2s}}$", "$r_{\mathrm{L}_{2Ss}}$", and "$r_{\mathrm{L}_{4Ss}}$", trip correctly. Additionally, the circuit breakers C_4, C_5, C_7, C_{11}, C_8, C_9, and C_{10} also operate correctly. In this case, the model from Ref. [28] is unable to obtain the correct results and requires a long solution time. By contrast, the method proposed in this paper provides accurate results and achieves a relatively shorter solution time.

Without loss of generality, we take the solution process of 9 fault cases in Table 4 as example to demonstrate the convergence of the objective function, as shown in Fig. 6.

It can be seen from Fig. 6 that, for simple fault cases, the objective function converges to a stable value only after 2 iterations, while for complicated fault cases, it also converges to a stable value after 3-4 iterations. It can be seen that the method proposed in this manuscript can quickly converge to a stable value in different cases. Compared with the results in Table 4, it can be verified that all diagnostic results are correct, and the longest diagnostic time is only 0.71s. Based on the results of Table 4 and Fig. 6, it can be seen that the linearized fault diagnosis model can directly use the advanced iterative algorithm embedded in GUROBI, which has significant advantages in solving 0-1 integer linear programming models in terms of speed, stability, and accuracy.

Furthermore, the applicability of the proposed method is analyzed with an IEEE-39 node system, as shown in Fig. 7. For the same diagnosis model proposed in this paper, various algorithms, such as the genetic algorithm, the particle swarm optimization algorithm, and the genetic taboo algorithm proposed in the literature [28], are compared with the GUROBI solver adopted in this paper. The parameters related to the genetic algorithm and particle swarm optimization algorithm are indicated above, and the parameters related to the genetic taboo algorithm are given as follows: the population size is set to 50, and the number of iterations is set to 20.

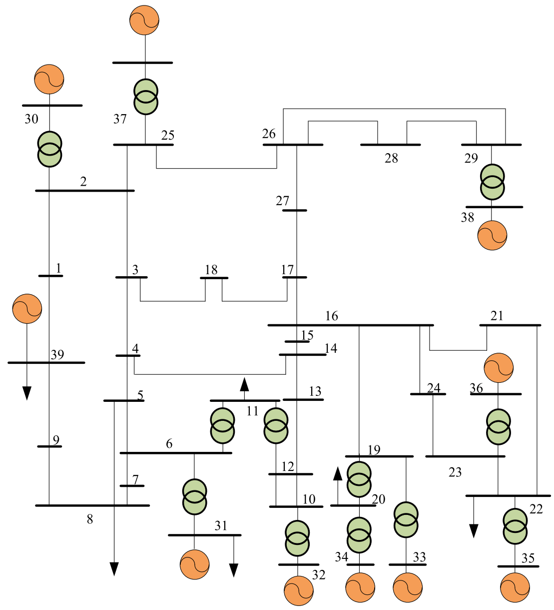

FIGURE 7. IEEE-39 node benchmark system for comprehensive fault diagnosis.

We set the following five fault examples: 1) Line L_{3-18} encounters a fault, the received alarm information includes the tripping of main protection r_{L3-18m}, r_{L18-3m}, and the operations of circuit breakers C_{3-18} and C_{18-3}; 2) Line L_{16-9} encounters a fault, the received alarm information includes the tripping of the first backup protection $r_{L16-19p}$ and main protection $r_{L19-16m}$, and the operations of the circuit breakers C_{16-19} and C_{19-16}; 3) Bus$_{26}$ encounters a fault, the received alarm information includes the tripping of busbar main protection r_{B26m}, and the operations of circuit breakers C_{26-29}, C_{26-28}, C_{26-25}, and C_{26-27}; 4) BUS$_{18}$ encounters a fault, the received alarm information includes the tripping of remote backup protection $r_{L3-18s}$and $r_{L17-18s}$, and the operation of circuit breakers C_{3-18} and C_{17-18}; 5) Lines L_{17-18} and L_{26-27} encounter faults, alarm information includes the tripping of the main protection $r_{L17-18m}$ and $r_{L26-27m}$, and the remote backup protection r_{L3-18s} and $r_{L17-27s}$, and the operations of circuit breakers C_{3-18}, C_{17-18}, C_{26-27}, and C_{17-27}. The diagnostic results of the involved algorithms are listed in Tables 5∼ 7. The diagnosis result is regarded as correct if the accuracy rate of the diagnostic result is higher than 90% according to the results of 500 repeated analyses.

In TABLE 5, both the genetic algorithm and the particle swarm optimization algorithm present misjudgments when diagnosing multiple faults in Example 5. In TABLEs 6 and 7, the accuracies of the genetic algorithm and particle swarm optimization algorithm are both below 95%, and the solving times are quite long. The accuracy of GATS reaches 96%, but the solving time is still relatively long. By contrast, the solver adopted in this paper not only has an accuracy of up to 98% but also greatly reduces the solving time compared to other algorithms.

As can be seen from Tables 6 and 7, fault diagnosis methods based on nonlinear integer programming models

TABLE 5. Comparison between the results of the GA, GATS, and PSO.

No.	GA	Evaluati on	GATS	Evaluat ion	PSO	Evaluatio n
1)	L_{3-18}	CORRE CT	L_{3-18}	CORR ECT	L_{3-18}	CORRE CT
2)	L_{16-9}	CORRE CT	L_{16-9}	CORR ECT	L_{16-9}	CORRE CT
3)	BUS$_{26}$	CORRE CT	BUS$_{26}$	CORR ECT	BUS$_{26}$	CORRE CT
4)	BUS$_{18}$	CORRE CT	BUS$_{18}$	CORR ECT	BUS$_{18}$	CORRE CT
5)	L_{26-27},L_{17-27}	WRON G	L_{17-18},L_{26-27}	CORR ECT	L_{26-27},L_{3-18},L_{17-18}	WRONG

TABLE 6. Evaluation results and execution times of TWO methods.

No.	Result from Propose d Model	Evaluation	Execution Times(s)	McCormick Envelope based Method	Execution Times(s)
1)	L_{3-18}	CORRECT	0.86	CORRECT	0.73
2)	L_{16-9}	CORRECT	0.52	CORRECT	0.48
3)	BUS$_{26}$	CORRECT	0.73	CORRECT	0.81
4)	BUS$_{18}$	CORRECT	0.91	CORRECT	0.87
5)	L_{26-27},L_{17-28}	CORRECT	1.02	CORRECT	1.05

and heuristic algorithms tend to produce incorrect results and have long solution times when solving complex faults. By contrast, the method proposed in this paper can correctly solve problems in most cases and reduce the solution time by more than two orders of magnitude compared to previous methods, making it better suited to meet the demands of fault diagnosis.

In order to further demonstrate the rationality and superiority of this method, it was compared with an advanced linearization method in the field of nonlinear optimization, i.e., McCormick envelope method.

McCormick envelope method is a convex relaxation method used for solving nonlinear programming problems, including the mixed integer nonlinear programming problems. Although McCormick envelope method is an approximate linearization transformation method, it can relax non-convex problems into convex problems. By this means, feasible solutions can be obtained using fewer branch-and-bound iterations, so as to use less computing resource and reduce computation time. From Table 6, it can be seen that the approximate linearization method based on McCormick envelope also achieves correct diagnosis of all simple and complex faults in Table 5, and the overall solution time is slightly shorter than the proposed method.

TABLE 7. Accuracy and solving times of the involved solving algorithmsn.

Method	Average Positioning Accuracy (%)	Average Execution Time (s)
Genetic Algorithm	92%	146.3
GATS	96%	65.7
Particle Swarm Optimization	93%	321.5
Proposed Solver	98%	1.06
McCormick Envelope based Method	97%	0.98

In Table 7, the results of more examples also indicate that the approximate linearization method based on McCormick envelope is slightly better than the method proposed in this manuscript in terms of solving time. However, in terms of diagnostic accuracy, it is 1% lower than the algorithm proposed in this manuscript. The reason may be that McCormick envelope is an approximate linearization method, while the method proposed in this paper is a completely equivalent linearization method. Therefore, when dealing with complicated fault diagnosis, the linearization method based on McCormick envelope has slightly lower accuracy than the method proposed in this paper. It is worth noting that, both methods are significantly better than heuristic algorithms.

Below, further comparisons are carried out to highlight the advantages of the proposed model. The diagnostic methods used are described in Ref. [7]; these methods involve high-performance artificial intelligence-based advanced fault diagnosis methods. Based on the IEEE-39 node system in Fig. 7, the investigated fault types are divided into two categories: simple faults and complicated faults. The simple fault scenario is a single-component fault with no distortion of the collected alarm information. The complicated fault scenarios include multiple components simultaneously encountering faults, a single component fault accompanied by missing or distorted information (with distortion rates ranging from 1% to 3%), and multiple components encountering faults simultaneously accompanied by information distortion. In the simulation tests, 100 simple faults and 230 complicated faults are examined. Among the 230 complicated cases, the proportion of the above three types of complicated faults is 90:90:50. The diagnostic results are shown in TABLE 8, where the execution time is the average solution time for all of the cases.

It can be seen from TABLE 8 that with regard to the execution time, both methods can accomplish the diagnosis process within approximately 1 s, while the method in Ref. [7] is slightly faster than the proposed method.

With regard to diagnostic accuracy, for single fault cases, both methods maintain 100% diagnostic accuracy. However, for complicated fault cases, the accuracy of the proposed method is 98.3%, which is slightly higher than the 97.0% accuracy of the method in Ref. [7].

TABLE 8. Comparison between the results of the proposed model and those of the model in Ref. [7].

Method	Average Execution Time (s)		Diagnosis Accuracy (%)	
	Single fault	Complicated fault	Single fault	Complicated fault
Proposed Model	0.81	1.31	100	98.3
Method in Ref. [7]	0.67	0.73	100	97.0

TABLE 9. Comparison of the results for different complicated faults.

No.	Fault type	Evaluation Results	
		Proposed method	Method in Ref. [7]
1)	Complicated fault with two information distortions	CORRECT	WRONG
2)		WRONG	CORRECT
3)		CORRECT	WRONG
4)		CORRECT	WRONG
5)		CORRECT	WRONG
6)	Complicated fault with three information distortions	WRONG	WRONG
7)		WRONG	WRONG
8)		WRONG	WRONG

To further analyze the characteristics of the two methods, all of the cases of misjudgments are enumerated for both methods in TABLE 9, while the detailed information of all the misjudgment cases can be found in TABLE 10 of the appendix.

It can be seen from TABLE 9 that there is a certain degree of overlap in the misjudgment cases of the two methods. Moreover, the misdiagnosed faults are all extremely complicated and accompanied by multiple information distortions. Among these faults, all of the cases where both methods a incorrectly were complicated faults accompanied by three information distortions. Among the five cases of complicated faults accompanied by two information distortions, the method in Ref. [7] misjudged four cases, while the proposed methods misjudged one case. In this sense, it can be concluded that the proposed method has better diagnostic accuracy than the method in Ref. [7] when dealing with complicated cases with multiple information distortions. This may be the model in Ref. [7] was not specifically designed for extremely complicated scenarios, resulting in a lack of sufficient data samples during the training phase and leading to a relatively lower fault tolerance performance than the method proposed in this paper.

In summary, the proposed method has a diagnostic accuracy of 80% when two of the inputs, protection information or circuit breaker information, are distorted. When there are three false input information, the proposed method will present incorrect results of diagnostics. It can be seen that the method proposed in this paper and the method in [7] cannot diagnose correctly in the case of three information distortion in the input information, but in the case of two information distortion, the method proposed in this paper has a high correct rate. The method proposed in this paper shows good diagnostic accuracy. Although slightly inferior to the

TABLE 10. Detailed diagnostic results of the proposed method and method in Ref. [7].

No.	Faulty components	Alarm Information [a]	Diagnostic Results		Evaluation Results	
			Proposed method	Method in Ref. [7]	Proposed method	Method in Ref. [7]
1)	$L_{16\text{-}21}$, $L_{16\text{-}17}$	$r_{L21-16m}$, $r_{L17-16s}$, $r_{L15-16s}$, $r_{L19-16s}$, $r_{L24-16s}$, $CB_{17\text{-}16}$, $CB_{21\text{-}16}$, $CB_{15\text{-}16}$, $CB_{19\text{-}16}$, $CB_{24\text{-}16}$	$L_{16\text{-}21}$,$L_{16\text{-}17}$	$L_{16\text{-}21}$	CORRECT	WRONG
2)	$L_{3\text{-}18}$, $L_{17\text{-}18}$	r_{L3-18m},$r_{L17-18s}$,$CB_{3\text{-}18}$, $CB_{17\text{-}18}$	$L_{3\text{-}18}$	$L_{3\text{-}18}$,$L_{17\text{-}18}$	WRONG	CORRECT
3)	$L_{26\text{-}28}$, $L_{26\text{-}29}$	$r_{L26-28m}$, $r_{L25-26s}$, $r_{L27-26s}$, $r_{L29-28s}$, $CB_{26\text{-}28}$, $CB_{29\text{-}26}$, $CB_{29\text{-}28}$, $CB_{25\text{-}26}$, $CB_{27\text{-}26}$, $CB_{25\text{-}26}$	$L_{26\text{-}28}$,$L_{26\text{-}29}$	$L_{26\text{-}29}$	CORRECT	WRONG
4)	$L_{26\text{-}28}$, $L_{26\text{-}29}$, $T_{29\text{-}38}$	$r_{T29-38m}$, $r_{L26-28m}$, $r_{L28-26m}$, $r_{L29-26m}$, $r_{L25-26s}$, $r_{L27-26s}$, $CB_{29\text{-}28}$, $CB_{28\text{-}29}$, $CB_{26\text{-}28}$, $CB_{28\text{-}26}$, $CB_{29\text{-}26}$, $CB_{25\text{-}26}$, $CB_{27\text{-}26}$	$L_{26\text{-}28}$,$L_{26\text{-}29}$,$T_{29\text{-}38}$	$L_{26\text{-}28}$,$T_{29\text{-}38}$	CORRECT	WRONG
5)	$L_{1\text{-}2}$, $L_{9\text{-}39}$	r_{L2-1m},r_{L39-1s}, r_{L8-9s},$CB_{2\text{-}1}$,$CB_{39\text{-}1}$,$CB_{8\text{-}9}$, $CB_{28\text{-}26}$	$L_{1\text{-}2}$,$L_{9\text{-}39}$	$L_{9\text{-}39}$	CORRECT	WRONG
6)	$L_{1\text{-}2}$, $L_{2\text{-}3}$, $T_{2\text{-}30}$	r_{T2-30m}, r_{L1-2m}, r_{L3-2m}, r_{L37-2s}, $CB_{30\text{-}2}$,$CB_{2\text{-}30}$,$CB_{2\text{-}1}$,$CB_{1\text{-}2}$,$CB_{3\text{-}2}$,$CB_{37\text{-}2}$	$L_{1\text{-}2}$,$L_{2\text{-}3}$	$L_{1\text{-}2}$,$T_{2\text{-}30}$	WRONG	WRONG
7)	$L_{23\text{-}24}$, $L_{4\text{-}14}$, $L_{25\text{-}26}$, $T_{2\text{-}30}$	r_{L4-14m}, $r_{L23-24m}$, $r_{L24-23m}$, $r_{L25-26m}$, $r_{L26-25m}$, r_{L14-4p}, $CB_{30\text{-}2}$, $CB_{2\text{-}30}$, $CB_{4\text{-}14}$, $CB_{23\text{-}24}$, $CB_{24\text{-}23}$, $CB_{25\text{-}26}$, $CB_{26\text{-}25}$, $CB_{14\text{-}4}$	$L_{4\text{-}14}$,$L_{25\text{-}26}$,$T_{2\text{-}30}$	$L_{4\text{-}14}$,$L_{25\text{-}26}$,$T_{2\text{-}30}$	WRONG	WRONG
8)	$L_{17\text{-}18}$, $L_{16\text{-}17}$, $L_{25\text{-}26}$, $T_{2\text{-}30}$	$r_{L18-17m}$, $r_{L25-26m}$, $r_{L26-25m}$, $r_{L16-17p}$, $r_{L27-17s}$, $CB_{30\text{-}2}$, $CB_{2\text{-}30}$, $CB_{18\text{-}17}$, $CB_{25\text{-}26}$, $CB_{26\text{-}25}$, $CB_{16\text{-}17}$, $CB_{27\text{-}17}$	$L_{16\text{-}17}$,$L_{25\text{-}26}$,$T_{2\text{-}30}$	$L_{17\text{-}18}$,$L_{17\text{-}27}$,$L_{16\text{-}17}$,$L_{25\text{-}26}$,$T_{2\text{-}30}$	WRONG	WRONG

A red color indicates that the uploaded alarm information is distorted.

method in [7] in terms of solving time, the diagnosis speed of the proposed method still meets the needs of on-site fault diagnosis.

Then we further investigate the potential impact of transient disturbances. To better clarify the potential impact, we divide this kind of disturbances into two types.

Type A of transient disturbances is generator or load tripping, which will not trigger protection action or circuit breaker tripping. Under this circumstance, the protection information system will not upload information to trigger the action of fault diagnosis system. Assuming that the fault diagnosis system is manually initiated and corresponding protection and circuit breaker information is obtained through other channels. Due to the absence of protection and circuit breaker action in the above situation, substituting the corresponding values into the objective function will definitely provide a fault-free diagnostic result, which means that such disturbances have no impact on the diagnostic result.

Type B of transient disturbances is the loss of power system synchronization. Under this circumstance, if the oscillation period is extremely short, causing the failure of the power swing blocking scheme of the line distance protection, the protection will mal operate and trip the corresponding line. Due to the consistency between the outlet information of the protection and the tripping information of the circuit breaker, the fault diagnosis system will provide an erroneous diagnosis result of the fault. That is to say, the model in this manuscript cannot be immune to tripping events caused by protection maloperation.

For instance, we assume the main protections $r_{\mathrm{L1-2m}}$ and $r_{\mathrm{L2-1m}}$ of line L_{1-2} malfunctioning due to the failure of power swing blocking scheme, causing the circuit breakers C_{1-2} and C_{2-1} to trip. In this case, line L_{1-2} is considered faulty based on both the protection and circuit breaker action information.

This is not a unique problem of the model in this manuscript, but a common problem of the classical fault diagnosis model based on equations (1) and (2) and all its derivative models. If we want to solve this problem, we need to redesign the objective function. Therefore, the limitations of the model in this manuscript are to be addressed by another study in the future.

VI. CONCLUSION

To address the difficulties faced by the traditional fault diagnosis analytical models in obtaining correct solutions for complex faults due to theoretical constraints, a new analytical fault diagnosis model for power grids is proposed to overcome the limitations of obtaining results that infinitely approximate the true solution.

The reason that the original model can be solved using only heuristic algorithms is revealed, and the model is therefore improved accordingly. By transforming the expression of the backup protection expectation from an equality constraint to an inequality constraint, the model is successfully reduced to a 0-1 integer linear programming problem. As a result, linear programming methods can be directly applied to obtain approximate optimal solutions. The results of extensive simulation tests demonstrate the effectiveness and advantages of the proposed model.

APPENDIX

See the Table 10.

REFERENCES

[1] Y. M. Park, G.-W. Kim, and J.-M. Sohn, "A logic based expert system (LBES) for fault diagnosis of power system," *IEEE Trans. Power Syst.*, vol. 12, no. 1, pp. 363–369, Dec. 1997.

[2] S. Lin, Z. He, and Q. Qian, "Review and development on fault diagnosis in power grid," *Power Syst. Protection Control*, vol. 38, no. 4, pp. 140–150, 2010.

[3] T. Zhang, X. Yan, R. Zhang, Q. Ye, and J. Ma, "Distributed architecture of power grid asset management and future research directions," *IEEE Access*, vol. 10, pp. 57588–57595, 2022.
[4] P. Zhang, N. Liu, B.-Y. Qu, J. Chang, J.-M. Xiao, Q.-F. Zhao, and L. Man-Man, "A novel smart grid fault diagnosis algorithm based on optimized BP neural network," *Int. J. Smart Grid Clean Energy*, vol. 7, no. 3, pp. 170–179, 2018.
[5] B. Xu, X. Yin, X. Yin, Y. Wang, and S. Pang, "Fault diagnosis of power systems based on temporal constrained fuzzy Petri nets," *IEEE Access*, vol. 7, pp. 101895–101904, 2019.
[6] L. Wang, Q. Chen, and Z. Gao, "Representation and application of fault diagnosis knowledge in power grid," *Proc. CSEE*, vol. 32, no. 5, pp. 85–92, 2012.
[7] X. Zhang, M. Du, Y. Wang, H. Zhang, and Y. Guo, "Research on power grid fault diagnosis based on a quantitative representation of alarm information," *IEEE Trans. Ind. Electron.*, vol. 70, no. 9, pp. 9582–9592, Sep. 2023.
[8] X. Zhang, R. Ding, Z. Wang, Z. Guo, B. Liu, and J. Wei, "Power grid fault diagnosis model based on the time series density distribution of warning information," *Int. J. Electr. Power Energy Syst.*, vol. 146, Mar. 2023, Art. no. 108774.
[9] X. Zhang, Z. Guo, Y. Zheng, J. Liu, P. Yan, and L. Zheng, "Power grid fault diagnosis using polar PMU data plots," *Int. J. Electr. Power Energy Syst.*, vol. 141, Oct. 2022, Art. no. 108148.
[10] Z. Wang, Z. Zhang, X. Zhang, M. Du, H. Zhang, and B. Liu, "Power system fault diagnosis method based on deep reinforcement learning," *Energies*, vol. 15, no. 20, p. 7639, Oct. 2022.
[11] J. Ji, Q. Chen, L. Jin, X. Zhou, and W. Ding, "Fault diagnosis system of power grid based on multi-data sources," *Appl. Sci.*, vol. 11, no. 16, p. 7649, Aug. 2021.
[12] T. Chen, D. J. Hill, and C. Wang, "Distributed fast fault diagnosis for multimachine power systems via deterministic learning," *IEEE Trans. Ind. Electron.*, vol. 67, no. 5, pp. 4152–4162, May 2020.
[13] P. Sun, X. Liu, M. Lin, J. Wang, T. Jiang, and Y. Wang, "Transmission line fault diagnosis method based on improved multiple SVM model," *IEEE Access*, vol. 11, pp. 133825–133834, 2023.
[14] A. Naimi, J. Deng, P. Doney, A. Sheikh-Akbari, S. R. Shimjith, and A. J. Arul, "Machine learning-based fault diagnosis for a PWR nuclear power plant," *IEEE Access*, vol. 10, pp. 126001–126010, 2022.
[15] H. Yu, L. Zhang, P. Zhao, Z. Liu, Z. Yang, M. Jin, and B. Hou, "Fault diagnosis of power transmission line based on elgamal encryption algorithm," in *Proc. IEEE 2nd Int. Conf. Electron. Technol., Commun. Inf. (ICETCI)*, Changchun, China, May 2022, pp. 953–957.
[16] M. Tan, J. Li, G. Xu, and X. Cheng, "A novel intuitionistic fuzzy inhibitor arc Petri net with error back propagation algorithm and application in fault diagnosis," *IEEE Access*, vol. 7, pp. 115978–115988, 2019.
[17] N. Shao, Q. Chen, Y. Dong, W. Ding, and L. Wang, "Power system fault diagnosis method based on intuitionistic fuzzy sets and incidence matrices," *IEEE Trans. Power Del.*, vol. 38, no. 6, pp. 3924–3938, Dec. 2023.
[18] A. K. Singh, R. Singh, G. Kumar, and S. Soni, "Power system fault diagnosis using fuzzy decision tree," in *Proc. IEEE Students Conf. Eng. Syst. (SCES)*, Prayagraj, India, Jul. 2022, pp. 1–5.
[19] Y. Li, N. Li, C. Li, D. Nan, and N. Li, "A novel fault diagnosis method based on differential current principle for power system," in *Proc. IEEE 6th Conf. Energy Internet Energy Syst. Integr. (EI2)*, Chengdu, China, Nov. 2022, pp. 1506–1511.
[20] F. Wen and Z. Han, "Fault section estimation in power systems using simulated evolution," *Trans. China Electrotech. Soc.*, vol. 10, no. 2, pp. 57–63, 1994.
[21] F. Wen and Z. Han, "Fault section estimation in power systems using genetic algorithm and simulated annealing," *Proc. CSEE*, vol. 14, no. 3, pp. 29–35, 1994.
[22] H. Weng, P. Mao, and X. Lin, "An improved model for optimizing power system fault diagnosis," *Autom. Electr. Power Syst.*, vol. 264, no. 7, pp. 66–70, 2007.
[23] D. Liu, Y. Guo, and S. Li, "Analytical model of power grid fault diagnosis considering main protection range of three-section line protection," *Power Syst. Technol.*, vol. 47, no. 5, pp. 1905–1911, 2023.
[24] W. Guo, Z. Liao, and F. Wen, "An analytic model for power network fault diagnosis with the temporal information of alarm messages taken into account," *Autom. Electr. Power Syst.*, vol. 404, no. 22, pp. 26–31, 2008.
[25] S.-P. Wang and D.-M. Zhao, "A hierarchical power grid fault diagnosis method using multi-source information," *IEEE Trans. Smart Grid*, vol. 11, no. 3, pp. 2067–2079, May 2020.
[26] Y. Jiang, "Data-driven probabilistic fault location of electric power distribution systems incorporating data uncertainties," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 4522–4534, Sep. 2021.
[27] S. Wang and D. Zhao, "Power grid fault diagnosis based on immune clonal constrained multi-objective optimization method," *Power Syst. Technol.*, vol. 41, no. 12, pp. 4061–4068, 2017.
[28] X. Lin, S. Ke, Z. Li, H. Weng, and X. Han, "A fault diagnosis method of power systems based on improved objective function and genetic algorithm-tabu search," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1268–1274, Jul. 2010.
[29] Y. Sun, Q. Chen, D. Xie, N. Shao, W. Ding, and Y. Dong, "Novel faulted-section location method for active distribution networks of new-type power systems," *Appl. Sci.*, vol. 13, no. 14, p. 8521, Jul. 2023.
[30] C. Wang, K. Pang, M. Shahidehpour, and F. Wen, "MILP-based fault diagnosis model in active power distribution networks," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 3847–3857, Sep. 2021.
[31] C. Wang, K. Pang, Y. Xu, F. Wen, I. Palu, and C. Feng, "A linear integer programming model for fault diagnosis in active distribution systems with bi-directional fault monitoring devices installed," *IEEE Access*, vol. 8, pp. 106452–106463, Aug. 2020.

ZHUONAN LIN was born in Wuhan, China, in 2004. He is currently pursuing the B.S. degree in process equipment and control engineering with Dalian University of Technology, Panjin, China. His research interests include advanced modeling theory and optimization algorithms and their application in industrial systems.

YONGXING WANG (Member, IEEE) was born in 1973. He received the B.S. degree from Hebei University of Technology, Tianjin, China, in 1993, the M.S. degree in electrical engineering from Huazhong University of Science and Technology, Wuhan, China, in 1996, and the Ph.D. degree in electrical engineering from Darmstadt University of Germany, Darmstadt, Germany, in 2005. His current research interests include intelligent detection of arc faults, cable insulation testing and state assessment, and aviation electrical system break simulation.

HAOQIAN XU is currently pursuing the master's degree with China Three Gorges University. He is also a Visiting Student with Huazhong University of Science and Technology. He is carrying out his research on power system relay protection and control.

FANRONG WEI received the Ph.D. degree in electrical engineering from Huazhong University of Science and Technology (HUST). His research has focused mainly on optimal power system/microgrid scheduling and protective relays.