Technique for optimization of diagnostic parameters composition for power systems objects

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Abstract A technique is proposed for optimization the composition of diagnostic parameters based on a combination of heuristic algorithms with the method of linear integer programming. The solution obtained using the heuristic algorithm with relatively small consumption of computational resources is taken as an initial one for optimization or checking the optimality of the composition of parameters using the linear integer programming method. The combination of a heuristic algorithm with the method of linear integer programming saves significant computational resources when searching for the optimal solution. The technique is aimed at minimizing costs when creating diagnostic support for monitoring performance and failure detection when considering the serviced and reconstructed electronic devices and equipment of power systems.

1. Introduction
Power systems are formed by technical complexes and operational personnel. Failures of technical complexes are dangerous due to serious consequences for the environment, and cause significant economic damage. Safety and cost reduction during operation of technical facilities are provided using a set of diagnostic tools. Decisions on diagnostic support taken at the facilities development stage of are justified by the choice of the optimal composition of diagnostic parameters (hereinafter referred to as parameters). The task of choosing the optimal set of parameters is solved when justifying the composition of control points, embedded and external diagnostic tools, development of algorithms and technological diagnostic processes. To optimize the parameters composition, the methods of combinatorial optimization (reduced search) and heuristic (without search) algorithms are used [1, 2].

Optimization of the parameters’ composition using reduced search having high power sets of types of technical states (hereinafter referred to as state types) and object parameters may require unacceptable consumption of computing resources (time, memory). The use of heuristic optimization algorithms saves computational resources, but does not guarantee obtaining an extremal value of the objective function. A contradiction arises that generates the problem of saving computational resources while optimizing the composition of parameters [3].

The solution of the problem is partly achieved by a compromise combination of a heuristic algorithm and a combinatorial optimization method. The idea is to obtain a solution, possibly not optimal, using a heuristic algorithm with relatively small expenditures of computational resources and accept it as an initial (reference) for optimization or checking the optimality using the combinatorial optimization method. The proximity of the reference solution to the optimum one results in search reduction using
the method of combinatorial optimization and in reduction of the computing resources cost [3]. The idea of combining a heuristic algorithm with the method of combinatorial optimization needs a quantitative justification.

The article proposes a technique of combining the linear integer programming method with binary variables and heuristic algorithms for optimizing the composition of monitored parameters. This technique is aimed at costs minimization when creating a diagnostic support for performance monitoring and failure detection when considering the serviced and reconstructed electronic devices and equipment of power systems.

2. Diagnostic model

Electronic devices and equipment of power systems are referred to as analog and digital objects for diagnostics. For such systems, the tolerance checking methods, including methods of exhaustive testing (transitions and units count, signature analysis) [1] are used for monitoring the operability and failure detection. The diagnostic object is defined by a set of types of the state \( E \) and a set of parameters \( U \) with known limiting values and costs for diagnostic support. The composition of parameters for monitoring the operating efficiency and failure detection is usually redundant.

The task of optimizing the redundant composition of parameters is proposed to be solved on the basis of a single diagnostic model of continuous and digital electronic objects, defining a binary relationship between types of state and alternative results of parameters control, for example, in the form of a dicotyled orgraph:

\[
G = (E, U_2, \varphi),
\]

where \( G \) is the orgraph designation; \( E \) is the set of vertices associated with the state types; \( U_2 \) is the set of vertices associated with valid and invalid parameter values; \( \varphi \) is the set of arcs connecting the vertices from the sets \( E \) and \( U_2 \).

Arcs of an orgraph give a binary relation

\[
\varphi: E \rightarrow U_2
\]

according to which each state type is assigned by alternative parameter values. If the state type \( E_i \) is manifested by a valid parameter value \( u_{j1} \) or an invalid parameter value \( u_{j0} \), then the corresponding vertices of the orgraph (1) are connected by an arc.

Orgraph (1) satisfies the following constraints:

\[
\varphi^{-1}(u_{j0}) \cup \varphi^{-1}(u_{j1}) = E, \ j = 1,2, \ldots, m,
\]

\[
\varphi^{-1}(u_{j0}) \cap \varphi^{-1}(u_{j1}) = \emptyset, \ j = 1,2, \ldots, m,
\]

\[
\varphi(E_i) \neq \varphi(E_k), i \neq k, \ i, k = 1,2, \ldots, n
\]

where \( \varphi^{-1}(u_{j0}), \varphi^{-1}(u_{j1}) \) are complete preimages, \( \varphi(E_i), \varphi(E_k) \) are images of the corresponding vertices; \( \emptyset \) is the void set; \( m \) is the amount of parameters; \( n \) is the number of failures.

Conditions (3) - (5) mean that for any type of state, the value of each parameter is known, not any type of state is simultaneously manifested as an invalid and valid parameter value, there are enough parameters to distinguish state types in pairs.

The formation of the orgraph (1) is carried out by expert methods on the basis of circuit simulation of the object. The dimension of the model is determined by the power of sets of types of state and parameters.

3. Method of optimizing the composition of parameters for performance monitoring

Condition (5) for failure detection is written as follows:

\[
\varphi(E_i) \neq \varphi(E_i), \ i = 1,2, \ldots, n,
\]
where $\varphi(E_0), \varphi(E_i)$ are the vertex images associated in the orgraph (1) to the working state and failure, respectively.

The sets $\varphi(E_i)$ that make up the images of failures differing from the operational state are not void:

$$|\varphi(E_i)| > 0. \quad (7)$$

The choice of the parameters composition for the detection of failures with minimal expenditures on the diagnostic support of the performance monitoring of the object modeled by the orgraph (1) is reduced to the problem of linear integer programming with binary variables:

$$\min \sum_{j=1}^{m} c_j x_j, \quad (8)$$
$$\sum_{j \in S_i} x_j > 0, \quad (9)$$

where $x_j$ is a variable that takes the value 1 if the parameter $u_j$ is selected to detect a failure and the value 0 otherwise; $c_j$ is the cost of diagnostic support for monitoring the parameter $u_j$; $S_i$ is the set of parameter numbers, the invalid values of which show a failure $E$.

Constraints (9) are formed on the basis of conditions (7). The number of constraints is equal to the number of failures.

The problem of linear integer programming with binary variables is solved using an additive algorithm with a Balas filter [5, 6]. As a filter, we take the costs for diagnostic support for monitoring parameters selected by the heuristic exclusion algorithm [7].

A set of parameters sufficient for detecting a failure is formed according to the heuristic algorithm by excluding vertices of the associated parameters with the highest diagnostic maintenance costs from the orgraph (1), excluding of which does not violate conditions (7).

Parameters are ranked in descending order of diagnostic costs. The parameter with the highest diagnostic maintenance costs is selected. The condition (7) is checked for all failures without taking into account the values of the selected parameter. If conditions (7) are satisfied, then the vertex associated with this parameter is excluded from the orgraph (1). In case of non-fulfillment of conditions (7) or after removing a vertex from the orgraph, the actions are repeated for the next parameter.

The upper limit of the number of computational operations for eliminating vertices from an orgraph and checking conditions (7) is estimated by the formula

$$(n + 1)m. \quad (10)$$

With an increase in the number of failures and parameters, the upper limit of the number of calculations increases slowly and almost linearly.

4. The method of optimizing the composition of the parameters to find the place of failure
Condition (5) becomes a condition for distinguishing failures in pairs for $i \neq 0, k \neq 0$. If this condition is met, then the symmetric differences of the sets $\varphi(E_i), \varphi(E_k)$, containing elements belonging exactly to one of the sets, are not empty:

$$|\varphi(E_i) \Delta \varphi(E_k)| > 0. \quad (11)$$

where $\Delta$ is the symbol of a symmetric set difference.

The choice of the composition of parameters for distinguishing failures in pairs with minimal cost for diagnostic support of finding the failure site of the object modeled by the orgraph (1) is reduced to the problem of linear integer programming with binary variables:

$$\min \sum_{j=1}^{m} c_j x_j, \quad (12)$$
$$\sum_{j \in S_{ik}} x_j > 0. \quad (13)$$
where \( x_j \) is a variable that takes the value 1 if the parameter \( u_j \) is selected to distinguish between failures and the value 0 otherwise; \( c_j \) is the cost of diagnostic support for monitoring the parameter \( u_j \); \( S_{ik} \) is a set of parameter numbers, the invalid values of which show difference between failures \( E_{ik} \).

Constraints (13) are formed on the basis of conditions (11). The number of constraints is calculated using the formula

\[
C_n^2 = \frac{n!}{2!(n-2)!}, \tag{14}
\]

where \( C_n^2 \) is the number of combinations of \( n \) by two.

The optimization problem (12), (13), like the problem (8), (9), is solved using an additive algorithm with a Balas filter. As a filter, we take the costs of diagnostic support for monitoring parameters selected by the heuristic exclusion algorithm [7].

A set of parameters sufficient to detect the place of failure is formed by heuristic algorithm by successively excluding from the orgraph (1) the parameters with the highest diagnostic maintenance costs, the exclusion of which does not violate conditions (5). The algorithm for eliminating redundant parameters for the search for a fault site is implemented similarly to the algorithm for eliminating redundant parameters for operability control.

The upper limit of the number of computational operations for eliminating vertices from a orgraph and checking conditions (5) is estimated by the formula

\[
(C_n^2 + 1)m, \tag{15}
\]

where \( C_n^2 \) is calculated by the formula (14).

With an increase in the number of failures and parameters, the upper limit of the number of calculations using the algorithm for eliminating redundant parameters for failure detection increases faster than the upper limit of the number of calculations using the algorithm for eliminating redundant parameters for performance monitoring.

5. Example and analysis of optimization results

Orgraph (1) for six failures and six object parameters is given in a tabular form (Table 1). Valid and invalid parameter values are denoted by 1 and 0, respectively. The set of parameters is ranked in descending order according to the cost of creating diagnostic software, amounting to 28 conventional units.

| E   | \( u_4 \) | \( u_5 \) | \( u_6 \) | \( u_2 \) | \( u_1 \) | \( u_3 \) |
|-----|---------|---------|---------|---------|---------|---------|
| \( c_j \) | 8  | 6  | 5  | 4  | 3  | 2  |
| \( E_0 \) | 1 | 1 | 1 | 1 | 1 | 1 |
| \( E_1 \) | 1 | 0 | 1 | 1 | 0 | 0 |
| \( E_2 \) | 0 | 0 | 0 | 0 | 1 | 1 |
| \( E_3 \) | 1 | 1 | 1 | 1 | 1 | 0 |
| \( E_4 \) | 0 | 0 | 0 | 1 | 1 | 1 |
| \( E_5 \) | 1 | 0 | 1 | 1 | 1 | 1 |
| \( E_6 \) | 1 | 1 | 0 | 1 | 1 | 1 |

The composition of the parameters for failure detection is reduced by the elimination algorithm by three redundant parameters. The remaining parameters (shown in bold in table 1) are sufficient for detecting a failure. The cost of diagnostic support for operability monitoring is 13 conventional units.
The cost of diagnostic software, obtained by the exclusion algorithm, is taken as a filter when optimizing the composition of parameters by the Balas algorithm. Object functions (8), constraints (9) and additional constraint (filter) are formed according to the table 1:

\[
\min (8x_4 + 6x_5 + 5x_6 + 4x_2 + 3x_1 + 2x_3),
\]

(16)

\[
x_5 + x_1 + x_3 > 0.
\]

(17)

\[
x_4 + x_5 + x_6 + x_2 > 0.
\]

(18)

\[
x_3 > 0.
\]

(19)

\[
x_4 + x_5 + x_6 > 0.
\]

(20)

\[
x_5 > 0.
\]

(21)

\[
x_6 > 0.
\]

(22)

\[
8x_4 + 6x_5 + 5x_6 + 4x_2 + 3x_1 + 2x_3 \leq 13
\]

(23)

Constraints are formed taking into account the fact that the refusal \( E_i \) is manifested by invalid values of parameters from the set \( \varphi(E_i) = \{u_{j0}\} \) and then \( S_i = \{j\} \). For example, according to the table 1: \( \varphi(E_1) = \{u_{50}, u_{30}, u_{30}\} \) and \( S_1 = \{5, 1, 3\} \).

The composition of the parameters for failure detection is reduced by the Balas algorithm by three redundant parameters. The optimal costs for the diagnostic support of the control parameters \( u_5, u_6, u_3 \) are 13 conventional units, which coincides with the result obtained by the elimination algorithm.

The problem of optimizing the composition of parameters is solved in a similar way to find the place of failure of an object specified by the model in the form of table 1. The optimal cost of diagnostic support for monitoring the parameters \( u_5, u_6, u_3, u_2 \) is 17 conventional units.

The upper limit of the number of calculations of the objective function and constraints in optimizing the composition of parameters for monitoring performance and failure detection is estimated using the appropriate formulas:

\[
2^m(n + 1),
\]

(24)

\[
2^m \left( \frac{n!}{2^{(n-2)} \cdot 1} \right)
\]

(25)

With an increase in the number of failures and parameters, the upper limit of the number of calculations of the objective function and constraints increases exponentially (Figure 1).
Figure 1. Diagram of the upper limit of the number of computational operations.

The number of calculations of the objective function and constraints when solving the problem of linear integer programming with binary variables according to the Balas algorithm is much less than the boundary values (Table 2). The use of a filter selected by the elimination algorithm, with a small dimension of the model (1), does not significantly reduce the number of calculations of the objective function and the limits of the Balas algorithm.

| Optimization task | Number of failures | Number of parameters | The upper limit of the number of calculations of the objective function and constraints | The number of calculations of the objective function and the optimization of the composition of the parameters | Minimum number of parameters | Minimum costs for diagnostic support of monitoring parameters, conventional units |
|-------------------|--------------------|----------------------|---------------------------------------------------------------------------------|---------------------------------------------------------------------------------|-----------------------------|------------------------------------------------------------------|
| Control of operability | 6 | 6 | 448 | 117 | 115 | 3 | 13 |
| Failure detection | 6 | 6 | 1024 | 166 | 159 | 4 | 17 |

After exclusion of $q$ redundant parameters from model (1), the number of parameters decreases to $m-q$, and the number of state types remains the same, equal to $n$. The upper limit of the number of calculations of the objective function and the limitations in optimizing the composition of parameters for monitoring performance or finding a place of failure is reduced to

$$\frac{1}{2^q} \times 100\%,$$ \hspace{1cm} (26)

The composition of parameters obtained by the elimination algorithm may not be optimal. The optimization of the composition of the parameter proceeds according to the Balas algorithm using the
model (1), from which the vertices associated with the redundant parameters found by the heuristic algorithm are excluded. The cost of diagnostic software obtained by the elimination algorithm is taken as a filter in the Balas algorithm. The number of calculations of the objective function and the constraints is less than the upper limit estimated by formula (26).

For example, for $n = m = 6$, the upper bounds, estimated by formulas (24) and (25), are 448 and 1024 calculations. After reducing the number of parameters by the elimination algorithm from six to three for performance monitoring and to four for searching for a fault, $q = 3$ and $q = 2$, the upper bounds are reduced to 56 and 256 calculations, that is, reduced to 12.5% and 25% respectively.

The optimization of the composition of the parameters for the performance control and the search for the place of failure is performed according to the following stages:

1) Object of diagnostics is modeled by orgraph (1);
2) Vertices corresponding to redundant parameters found by the heuristic algorithm are excluded from the orgraph, and the costs of diagnostic support for monitoring the remaining parameters are determined;
3) On the basis of the obtained model, the objective function, the constraints of the linear integer programming problem and the filter for the Balas algorithm are formed;
4) The linear integer programming problem is solved using an additive algorithm with a Balas filter.

The proposed technique is applicable to optimize the composition of the monitored parameters by combining heuristic exclusion algorithms not only with the Balas method, but also with other mathematical programming methods, for example, with the branch and bound method.

6. Conclusion

The obvious idea of combining a heuristic algorithm with a method of combinatorial optimization, which received a quantitative justification in the article, can become one of the possible compromise between the requirements of reducing complexity and achieving optimal decision making. A slight increase in computational resources in terms of the implementation of a heuristic decision-making algorithm is compensated by a significant decrease in computational resources in terms of achieving an optimal solution by the method of mathematical programming. As a result, the cost of computing resources to achieve the optimal solution is significantly reduced. At the same time, the combination of a heuristic algorithm with the combinatorial optimization method only partly solves the problem of saving computational resources while optimizing the composition of parameters. Optimization of the composition of object parameters with a large, albeit limited by a heuristic algorithm, set of failure sets and parameters is achieved at the cost of high computational resources.

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