A Method of Task Allocation for Collaborative Diagnosis

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Abstract In the domain of collaborative diagnosis which joined with multi-resource, on account of equipment's complexity and diagnosis resource's heterogeneous, diagnosis task allocation should be self-adaptive. This requirement can be satisfied with an static and dynamic integrated task allocation method, in the static allocation method, diagnosis task relation model was established with equipment's qualitative model and fuzzy relation matrix, diagnosis path planning was realized by improving D-**algorithm**, and multi-**constraint** integer **programming** was used to resource **allocation**; In the dynamic method, an extended contract net method was introduced, which based on utility and negotiation. Then, the validity of this method has been validated within an **engineering equipment fault** diagnosis instance. The conclusion summarizes this method and points out its further development.

1. Introduction

Currently, confronted with diagnosis and maintenance puzzledom of complex equipment, multi-resource (remote) collaborative diagnosis has been an feasible way, and among them, collaborative diagnosis task allocation is a process which allocating diagnosis task to available diagnosis resource and harmonizing task executive sequence of various resources. On account of distributed、heterogeneous、dynamic and extensible characteristics of diagnosis resource, distributed and appropriate resource supervising strategy is needed to assist every member share resource efficiently. As an NP problem, collaborative diagnosis task allocation can be classified into graph theory-based method、heuristic method and intelligent allocation method; Considering distributed and hierarchy qualities of equipment's structure and function, familiar method is task-tree method which decomposes function、structure or fault of equipment dendritically from the top-down[1], this method is understandable but its consideration on some diagnosis constraints problem is prone to subjective.

An idiographic diagnosis task allocation process includes: determining current diagnosis task objective, task decomposing, customizing task execution order, choosing resources, carrying out task and administering resources. Textual collaborative diagnosis task allocation method, firstly, utilizes fuzzy relation matrix of equipment to establish task relation graph model, then employs critical path algorithm on task relation graph to carry through path planning, moreover, multi-constraint integer programming method is used to confirm favorite diagnosis resources. Otherwise, an extended contract net is introduced to consider path planning and resource allocation flexibly, as figure 1 shows. Path planning and resource allocation are linked closely but their attention are different, path planning belongs to the category of task relation graph, it pays attention to execution order of tasks; However, resource allocation (optimization) aims at diagnosis resources alliance, it pays attention to how to ascertain task's execution resource.

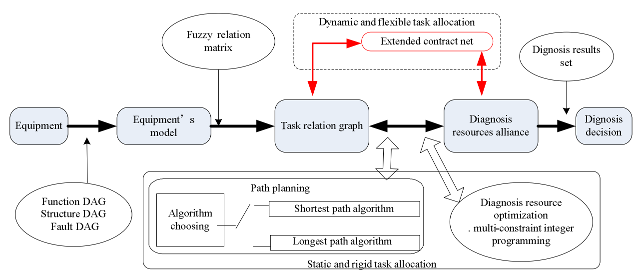

Fig. 1. An integrated diagnosis task allocation framework

2. Static diagnosis tasks-resources layouting

Diagnosis task allocation takes collaborative diagnosis task as its input, bases on diversified correlative information, takes diagnosis constraints condition into account, and regards task allocation target as a guide of decision optimization, to further realize holistic advantage of collaborative diagnosis. Suppose $Symptom=\{Sym(i)|i=1,2,\ldots,n\}$ as observable fault symptoms currently, *Source={Sou(j)|i=1,2,…,m}* as all potential fault sources set, *Dec=[0,1]*, × is cartesian product, target function R is task allocation's optimization index, then uncertain task allocation can be described as $Task-ALLOC:\{\prod_{i=1}^{n} Sym(i)\times Dec(i)\to\prod_{j=1}^{m} Sou(j)\times Dec(j)\}\mid R$.

2.1. Diagnosis task relation modeling

2.1.1 Basic knowledge given

Collaborative diagnosis is a dynamic changing process, and can be parallel implemented only when the diagnosis solving process is refined to an operational degree based on artificial intelligence reduction methods. So the relation model of diagnosed object should be builded up firstly, and related knowledge to be used are as follows:

(1) Relation and relation concept space. Relation is generalization and abstraction on interaction and interrelation of material、energy and information between elements or in an element internal. Relation includes two aspects: dynamic and static relation.

Then relation can be divided into n layer concept space $R^{(1)},R^{(2)},\dots,R^{(n)}$. The i-1 layer relation can be described by i layer sub relation from different sides. Every sub relation of the bottom layer $R^{(n)}$ are accepted as basic relation.

(2) Fuzzy relation and its matrix denotation. Generally, instances are a limited set $A=\{x_1,x_2,\dots,x_n\}$ to describe basic relation $R_i^{(n)}=\{R_1^{(n)},R_2^{(n)},\dots R_m^{(n)}\}$ between two elements (S_q,S_p) of equipment system $S=\{S_1,S_2,\dots,S_m\}$, and for every fuzzy sub set $R_i^{(n)}=\sum_{x_j\in A}[\mu_{R_i}(x_j)/x_j]$ in A, instance x_j of A describes relation between two elements (S_q,S_p) relativing to $R_i^{(n)}$ in some degree, its membership degree can be denoted with membership function: $\mu_{R_i}(S_q,S_p)=\sum_{j=1}^{n} C_j\cdot\mu_{R_i}(x_j)$ (1)

$0\le C_j\le 1$ are weight coefficient and their sum equals to 1. Fuzzy relation matrix of sub relation $R_i^{(n)}$ in n layer relation concept space is: $[R_i^{(n)}]=[\mu_{R_i}^{(n)}(S_q,S_p)]$.

2.1.2 Diagnosis task relation modeling based on function and structure of equipment

When modeling based on function and structure of equipment, accessible diagnosis resource can be viewed as organic composition; After diagnosis basic element formed, then we can analyze and coordinate the interactional instance between diagnosis basic elements and form basic instance set.

In order to establish fuzzy relation matrix, it's first needed to confirm relation close degree function value among basic elements using instances and their characteristic value, then collect all the above function value to compose a fuzzy relation matrix. Considering basic instances and their characteristic value are multifarious and inconsistent, so it's necessary to formulate an actual operable uniform solution criterion if we want to realize clustering transform. And the steps are as follows:

(1) List all the instances and their characteristic value among basic elements. Adopt K-W computing method to analyze and reconstruct few excellent new characteristic.

(2) Form basic relation with instances set and their characteristic value. After above characteristic extraction, take every instance as a sample, and use ISODATA technique to classify instances into k classes briefly, and solve out every kind of condensation point coordinate $v_i(i=1,2,\dots,k)$ and every instance's membership function $\mu_{v_i}(x_j)$ relativing to V_i. Condensation point value reflect the similarly degree among basic relations in a relation concept space.

(3) Establish standard relation-tree structure. Based on the similarly degree among basic relations, adopt above ISODATA technique sequentially to classify basic relations into some sub classes, and solve the new condensation point coordinate, this can form sub relation of lower layer relation concept space. And so on, go to next step until all basic relations have been clustered in one class.

(4) Determine every branch contribution rate of standard relation-tree. In standard relation-tree, the contribution rate calculation formula of lower layer to higher layer is:

$$u_{oj} = (d_{oj} / \sum_{p=1}^{n} d_{op}) \cdot K_{oj} \tag{2}$$

$\sum u_{oj} = 1$ and n is sample amount, d_{oj} is the distance from sample point to condensation point v_o, K_{oj} is weight coefficient.

(5) Establish fuzzy relation matrix. When calculating relation close function value among basic elements based on standard relation-tree, it's first needed to calculate the amount of instances between basic elements which indicated as E_{ij}, then formula (2) changes into:

$$\mu_{R_i}(S_i, S_j) = [\sum_{p=1}^{E_{ij}} E_{x_p} \cdot \mu_{R_i}(x_p)] / E_{ij} \tag{3}$$

x_p is corresponding instance between basic elements S_i and S_j, E_{x_p} is the number of this instance.

According to contribution rate u_{oj} solved from formula (2)、formula (4) and above constructed standard relation-tree, solve out relation degree value among basic elements from the bottom up and layer by layer, then fill finally results into formula (1) to form fuzzy relation matrix, here:

$$\mu_{R_O^{(v)}}(S_i, S_j) = \sum_{m=1}^{n} u_{om} \cdot \mu R_{om}^{(v)}(S_i, S_j) \tag{4}$$

(6) Mapping diagnosis task relation model from fuzzy structure、function relation matrix of equipment, and import virtual node to realize layered and modular model. Then diagnosis task relation model can be defined as a diagnosis task relation graph with m edges and n nodes: DTRG={V,E}$_{mn}$.

2.2. Diagnosis task path planning

After fixed on the execution relation of diagnosis task, considering task relation diversity of DTRG, in order to enhance the consistency of diagnosis problem solving, it's needed to construct a series of action rule aiming at corresponding diagnosis task execution process. Diagnosis path planning includes some steps such as path building, path arranging, path identifying. Critical path method can be used to make certain task execution order.

In a DTRG with m edges and n nodes, path $P = \{V_i, ..., V_j\}$, a path length $PL = \{\sum_{j=1}^{m} \sum_{i=1}^{n} (V_i + E_{ij}) \mid P\}$; Longest (Shortest) critical path is a series of paths which average execution benefit (or cost) is maximum (minimum) when diagnosis task is performing; So critical path can be classified into longest critical path method (LCPM) and shortest critical path method (SCPM), the difference between them lies on the type of edge weight value represented, when weight value is benefit type index, such as task significance、task success probability or diagnosis benefit etc, LCPM should be adopted; Reversely, when weight value is cost type index, such as diagnosis time、cost, SCPM should be adopted. These path planning methods can be realized with D-algorithm[2] and so on.

2.3. Resource allocation with multi-constraint

Typical task allocation is under the given situation of task and available diagnosis resource, and task associates with resource according to the capability requirement of task and resource's function, this conjunction (mapping) can invocate suitable resources to organize and accomplish their diagnosis task in different phases by satisfying some constraints. Known that a diagnosis task has been decomposed into *n* sub tasks and *m* diagnosis resources can be acquired, then diagnosis task allocation constraints set can be described as $C = \{C_a, C_c, C_t, C_s\} = \{(a_{ij})_{mn}, (c_{ij})_{mn}, (t_{ij})_{mn}, (s_j)_{1n}\}$, refer to table 1, the coefficient of constraints can be confirmed by following rules:

·Diagnosis capability coefficient a_{ij}—according to historical diagnosis cases matching: Has accomplished same task successfully, rank as I, or else rank as VI; Has accomplished analogical task successfully, rank as II, or else rank as V; Has accomplished similar task successfully, rank as III, or else rank as IV.

· Diagnosis cost coefficient c_{ij}—according to diagnosis cost evaluating: when cost is lowest、lower、low、high、higher、highest, coefficient c_{ij} can be ranked as I、II、III、IV、V、VI in turn.

· Diagnosis time coefficient t_{ij}—according to diagnosis time evaluating: when diagnosis time is shortest、shorter、short、long、longer、longest, coefficient t_{ij} can be ranked as I、II、III、IV、V、VI in turn.

· Diagnosis urgency coefficient s_j—according to fault influence degree evaluating: Instantly execute, rank as I; Execute in an hour, rank as II; Execute in a working day, rank as III; Execute in three working day, rank as IV; Execute in seven working day, rank as V; Or else ran as VI.

Table 1 Fuzzy evaluating the coefficient of constraints

Coefficient	Fuzzy evaluation rank					
	I	II	III	IV	V	VI
a_{ij}	0.9	0.7	0.5	0.3	0.2	0
c_{ij}	1	0.8	0.6	0.4	0.2	0
t_{ij}	1	0.8	0.5	0.4	0.3	0.1
s_j	1	0.8	0.6	0.4	0.2	0

Consequently, a balanced matrix *a-c-t* of diagnosis resource constraints can be described as $B=(b_{ij})_{mn}=[\lambda_1 a_{ij}+\lambda_2 c_{ij}+\lambda_3 t_{ij}]_{mn}$, $\lambda_i \in [0,1]$ reflects the preference of every constraints coefficient; Then diagnosis resource optimization model is $\{\max \sum_{j=1}^{n} s_j(\sum_{i=1}^{m} b_{ij}x_{ij})\} \mid s.t. \sum_{i=1}^{m} x_{ij}=q_j, \sum_{j=1}^{n} x_{ij}\le 1$, q_j denotes the amount of diagnosis resources when executing task j, and if resource i participates in task j then $x_{ij}=1$, or else $x_{ij}=0$. The optimization model also is an typical 0-1 integer programming problem which can be solved by branch and bound method [3].

3. Diagnosis task dynamic allocation based on extended contract net

Foregoing static task allocation method is tougher sometimes, it's proper to be adopted when diagnosis center is familiar with the fault type and diagnosis environment of equipment, or DTRG is legible and concise. Whereas, the flexible and dynamic task allocation method based on Extended Contract Net (ECN) can be adopted even facing new fault, or diagnosis center isn't familiar with new joining diagnosis resource or DTRG is complex and enormous. Compared with classical contract net, ECN imports into diagnosis task case reasoning; Moreover, in view of the load balance of diagnosis and the efficiency of collaborative diagnosis process, threshold limitation on quantity of participant diagnosis resource alliance $R=\{R_1,R_2,\ldots,R_n\}$ has been introduced and named $|R|$, and $|P|$ denotes the maximum of diagnosis resource can deal with task bidding simultaneously[4], $|R_{Ci}|$ is current employer amount of R_i, the payment form of contract is utility which can be described with utility function. Then dynamic task allocation method is described as following:

(1) Diagnosis task supervision center choose a diagnosis task T_i;

(2) According to task similarity degree calculating formula $Similar(T_1,T_2)=\sum_{i=1}^{m}\sum_{j=1}^{n} W(A_{1i},A_{2j})\times Equal(V_{1i},V_{2j})$, task T_i is compared with each task records in task case base in turn[5], if satisfactory case can be found out then turn to step (4); If failed then turn to step (3);

(3) Initialize new diagnosis task, predetermine $|R|$ and its rewards or punishments factor, minimize utility value of diagnosis resource, turn to step (5);

(4) Based on descriptive information of this diagnosis task, adopt multi-constraint decision method which can be referred to in section 2.3 to quantify every resource utility value $Man\_Utility_{ij}=Tr(R_{ij})\cup Man\_Cost-OP^e$, $Tr(R_{ij})\in[Tr_l,Tr_h]$ is trust degree of supervision center on resource R_i to accomplish task T_j , and $Man\_Cost=\varphi_{ij}(bC_a,dC_s,eC_t,fC_c)$, b、d、e、f are all constants, $\varphi_{ij}()$ is a unified transform function of different dimensional parameters and it's usual a complete replacement function; OP^e is final transaction price;

(5) Center sends out bidding document to $|R|$ diagnosis resources satisfied the quantized constraint conditions based on utility value sequence from high to low; Then the $|R|$ diagnosis resources bid or reject on the basis of its utility function $\mathrm{Re}s\_Utility_{ij} = OP^{e} - \cos t\_\mathrm{Re}s_{ij}$, here , $\cos t\_Res_{ij} = Com\_Cost + \mathrm{Re}s\_Cost + Exp\_Punish + \mathrm{Re}s\_Load$, Com_Cost is necessary communication cost of accomplishing task, $\mathrm{Re}s\_Cost = \sum_{i=1}^{n} a_i \mathrm{Re}s_i\_Cost$ is some costs such as human resource、basic consumed material、devices of task-performing, Exp_Punish is risk cost under rewards and punishments mechanism, $\mathrm{Re}s\_Load$ is current load conditions of bidding resource;

(6) Center negotiates with relevant diagnosis resource in the foundation of bidding document in turn, negotiation behavior includes quotation、anti-quotation、refusal and acceptance etc. If negotiation is successful then determine most satisfactory diagnosis resource but which isn't sure to be optimal, and after signed a contract, turn to step (8); If there hasn't available resource then demands work over task decomposing;

(7) After signed contract, corresponding diagnosis resource executes diagnosis task and adjusts its threshold $|R_{Ci}|$ using threshold adjusting rule;

(8) Diagnosis resource returns its diagnosis result to center, and then center evaluates the result and adjusts its trust degree of this diagnosis resource. $evl(R_i, T_j)$ is used to represent evaluation value of center to diagnosis resource R_i which has accomplished task T_j, V_H is evaluation threshold when task has been accomplished successfully, λ_{ij}^{award} is reward factor, and λ_{ij}^{punish} is punishment factor, so

$$Tr(R_{ij}) = \begin{cases} \min\{Tr_h, Tr(R_{ij}) + \lambda_{ij}^{award}\}, evl(R_i, T_j) \geq V_H \\ \max\{Tr_l, Tr(R_{ij}) + \lambda_{ij}^{punish}\}, evl(R_i, T_j) < V_H \end{cases};$$

(9) Tidy up and store this diagnosis task case into case base; End or turn to step (1).

4. An diagnosis task allocation example of engineering equipment

Engineering equipment possesses movable、complex working environment、strict safety requirements and other features. Here take one braking system of concrete transport car composed by Mitsubishi chassis as an example, it's a pneumatic-hydraulic brake acting on all wheels, figure 2 shows its component structure graph.

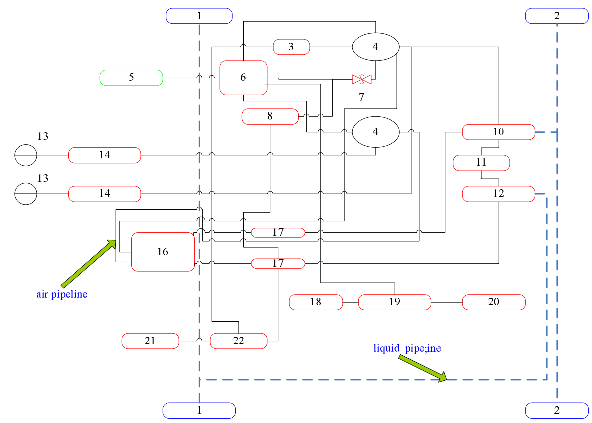

Fig. 2. An structure graph of pneumatic-hydraulic braking system

Primary braking faults include braking failure、ineffective、lagging and sideslip. In the cause analysis of braking ineffective[6], only suspected causes of pneumatic、hydraulic system have already as many as 28 items. Based on figure 2 and above modeling method, standard relation-tree structure and every part contribution rate of braking system diagnosis task relation model DTRG can be gained as figure 3; This graph reflects relation clustering result, from lower layer to high layer, the closer relation with basic element, the task function which represented with diagnosis basic element should be more ahead arranged in planning paths.

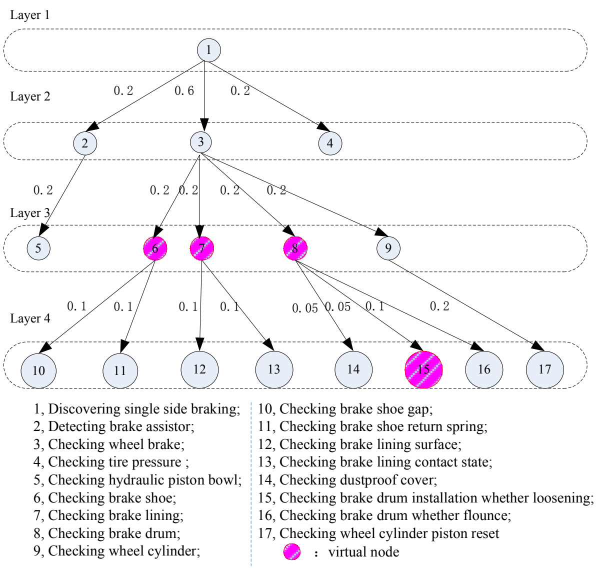

Fig. 3. The diagnosis task relation graph of braking system

Then final critical path can be listed and critical task $T=\{T_3,T_9,T_{17}\}$ by adopting path planning algorithm in section 2.2, diagnosis resources can be confirmed via quantifying and solving some optional constraint coefficients of diagnosis resource. Neglect task urgency constraint coefficient s_j and supposes participant diagnosis resources include brake shoe detecting instrument (five-wheel meter)、remote hydraulic pump spectrum analysis service resource、maintenance personnel、remote diagnosis expert, namely $H=\{H_f,H_w,H_m,H_e\}$, diagnosis task-capability constraints matrix $U_a=[\{0,0.2,0.7,0.9\},\{0,0.9,0.3,0.7\},\{0.9,0.3,0.2,0.9\}]^T$, diagnosis cost constraint matrix $U_c=[0.4\ \ 0.8\ \ 1\ \ 0.2]$, diagnosis time constraint matrix $U_t=[0.8\ \ 0.5\ \ 0.5]^T$, and then *a-c-t* constraint balanced matrix $B=[a_{ij}c_jt_i]_{mn}$ $=[\{0,0.13,0.56,0.14\},\{0,0.36,0.15,0.07\},\{0.18,0.12,0.1,0.09\}]^T$. Substitute above matrix into resource optimization model and solve it by branch and bound method. So proper diagnosis resources have been confirmed: maintenance personnel checks brake ($T_3 \rightarrow H_m$), remote hydraulic pump spectrum analysis service resource diagnoses pump ($T_9 \rightarrow H_w$), brake shoe detecting instrument checks piston ($T_{17} \rightarrow H_f$).

Similarly, after employed ECN task allocation method, the compared result of it with classical contract net has been showed as figure 4, ECN is wholly better in diagnosis task execute quality、cost、speed aspects owing to the amount and intention of bidding documents has been improved, then communication、negotiation cost have been reduced while the favorite diagnosis resource selected probability has been enhanced.

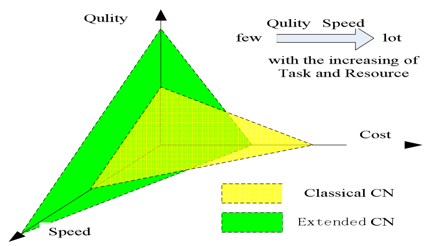

Fig. 4. The performance compared 3D graph between ECN and CCN

5. Conclusion

This paper has solved coordination problem in multi-resource collaborative diagnosis by adopting static、dynamic task allocation method. Static method includes diagnosis task relation establishing、diagnosis task path planning and diagnosis resource optimization three parts; This method has the virtue of clear framework and easy realization, and its next key issue is how to interact with existent diagnosis knowledge, namely information mining, here, PCA or Rough Set theory can be used as its treatment front-end. Dynamic method applies humanized extended contract net; Further, it's needed to study the seamless connection、holistic realization and other attention point between supervision center and other system (ERP、diagnosis decision center etc.) when take supervision center as a MAS.

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