REASONING IN INTELLIGENT DIAGNOSIS SYSTEMS

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Abstract: The paper is devoted to research and modeling reasoning based on Assumption-based Truth Maintenance Systems (ATMS) and reasoning by analogy in intelligent diagnosis systems. The new heuristic approaches of current measurement point choosing on the basis of supporting and inconsistent environments are presented. Reasoning by analogy method is viewed. This work was supported by the Russian Fund for Basic Research.

1 INTRODUCTION

The diagnostic systems are one of the most actively used systems in technical areas: electronics engineering, motor industry, robotics, space vehicles, thermal and atomic power stations and many others. Many diagnostics problems require building the behaviour prognoses, the work with contradictions and defaults, effective treatment of new facts and assumptions. The typical problem of diagnostics is to find a fault (faults) of a diagnosed device on the basis of some set of observations.

At first model-based diagnostics on the basis of Assumption-based Truth Maintenance Systems (ATMS) and heuristic methods of choosing a measurement point in a diagnosed device are viewed. Modeling results of the best measurement point choosing for the 9-bit parity checker are given. Then we consider case-based reasoning by analogy method for diagnostics of complex object states.

2 MODEL-BASED DIAGNOSIS

The generalized problem of diagnostics can be formulated as follows. There is a device exhibiting an incorrect behaviour. The device consists of components, one or several of which are not working properly what is the reason of incorrect behaviour. There is a structure of connections between components and a possibility to get measurements on their inputs and outputs. It is necessary to determine what of components are faulty with minimal resource expenses.

There are several approaches to a solution of the given problem one of which is model-based diagnosis (Clansey, 1985; de Kleer et al., 1987; Forbus et al., 1993). This approach is based on the knowledge of device component functionality. The model of a device is a description of its physical structure, plus the models for each of its components. A compound component is a generalized notion including simple components, processes and even logical inference stages.

Model-based diagnosis process is the comparison of predicted device behavior with its observed behaviour. It is supposed, that the model is correct, and all differences between device behaviour and a device model indicate availability of broken components.

Main advantages of the model-based approach:

- Diagnosing the multiple faults;
- Unexpected fault recognition;
- A precision of a component model description does not depend on the expert experience;
- A possibility of new device diagnosing;
- Multiple using the models;
- Detailed explanations.

3 ASSUMPTION-BASED TRUTH MAINTENANCE SYSTEMS

For building a prognosis network, a component

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behaviour model, finding minimal conflicts characterizing uncorrespondence of observations with prognoses and minimal candidates for a faulty, it is profitable to use possibilities given by ATMS (de Kleer et al., 1987; Forbus,1993).

The truth maintenance systems (TMS) are the systems dealing with the support of a coherence in databases. They save the assertions transmitted to them by a problem solver and are responsible for maintaining their consistency. Each assertion has the justification describing what kind of premises and assumptions this justification was obtained. The environment is a set of assumption.

The inference of an inconsistency characterizes assumption incompatibility within the presuppositions of which this conclusion was made. Also there is introduced the environment set which contains some inconsistency (de Kleer et al., 1986). The sets of inconsistency environments *E1, E2 ,…, Em* are *Nogood={E1, E2 , ... Em}*. A consistent ATMS environment is not *Nogood*.

There are the following correspondences between ATMS and the model-based diagnosis approach:

· ATMS premises – an observed device behaviour;

· ATMS assumptions – components of a device;

· inferred ATMS nodes – predictions of an diagnostic system;

· *Nogood* - the difference between predicted and observed device behaviour.

4 THE CURRENT MEASUREMENT POINT DETERMINATION

One of the key aspects of the model-based fault search algorithm is to determine the optimal current measurement in a diagnosed device (de Kleer, 1987). Efficiency of the current measurement choosing allows essentially reducing a decision search space while the inefficiency of choice will increase an operating time, the space of a searching algorithm, and also require additional resource spends to implement a measurement.

The best measurement point in a diagnosed device is a place (point) of measuring a value giving the largest information promoting the detection of a set of fault components at minimal resource spending.

One of the best procedures for reducing resource expenses is to produce the measuring giving the maximal information concerning predictions made on the basis of the current information on a system.

Heuristic Methods of Choosing a Measurement Point

The purpose of the best choosing a measurement point is to derive the maximal component state information. After each measuring there is a confirmation or refutation of prediction values in a point of measurement. So, it is possible to use the following aspects (Vagin et al., 2006 a,b,c):

- knowledge about environments that support predicted values in the measurement points which can be confirmed or refuted;
- knowledge about inconsistent environments;
- knowledge about coincided assumptions of the inconsistent environments.

Knowledge About Supporting Environments

The diagnostic procedure constructs predictions of values for each device point with the list of environments in which the given prediction is held. The list of environments represents assumption sets about correctness of corresponding device components.

The mismatch between observations and predictions speaks about a fault in a device. Based on measured observations additional predictions of values are formed. In general, it is obtained some set of predictions with appropriate environments.

As we are interested with a measurement point with the greatest information on failure the point is selected from a quantity of assumptions.

Designate an environment set as *Envs*(*x*). Let's introduce the function *Quan*(*x*), by which we will designate the information quantity obtained at measuring values in the point *x*.

If the environment *J* represents a unique assumption, then obviously the set cardinality will be equal 1: $|J| = 1$. The information quantity obtained from such environment is equal to 1. If the environment consists more than one component the information quantity obtained at confirming or refuting a value is less because we have knowledge not about a concrete valid / fault components but about a component set among of which are faulty. Therefore the information quantity obtained from a environment consisting of more than one assumption, we heuristically accept equal to half of set cardinality. Thus the function *Quan*(*x*) is:

$$Quan(x) = \sum_{\substack{J_i \in Envs(x) \\ |J_i|=1}} |J_i| + \sum_{\substack{J_j \in Envs(x) \\ |J_j|>1}} \frac{|J_j|}{2} \qquad (1)$$

Summing is produced on all possible values in the point *x*.

Points with the greatest value of the function *Quan*(*x*) have the greatest priority of a choice. We will call the given method of choosing a measurement point as SEH (Supporting Environment Heuristics).

Knowledge about the Sets of Inconsistent Environment

As a result of each measurement there is a confirmation or refutation of some prediction. The environments $E_1, E_2, \ldots, E_m$ of refuted prediction form the set $Nogood = \{E_1, E_2, \ldots, E_m\}$. It can be used for directional searching for more precise definition what kind of components from *Nogood* is broken.

Obviously the more of the components from *Nogood* are specified by measuring a value in some device point the more the information about which components of *Nogood* are broken will be obtained. For using this possibility, it is necessary to take the intersection of each environment from *Envs(x)* with each set from *Nogood*:

$Envs(x) \cap Nogood = \{A \cap B : A \in Envs(x), B \in Nogood\}$.

For this approach the equation (1) can be changed as follows:

$$QuanN(x) = \sum_{\substack{J_i \in Envs(x)\cap Nogood \\ |J_i|=1}} |J_i| + \sum_{\substack{J_j \in Envs(x)\cap Nogood \\ |J_j|>1}} \frac{|J_j|}{2}$$

Points with the greatest value of function QuanN(x) have the greatest priority of a choice. We will call the given method of choosing a measuring point as SIEH (Supporting and Inconsistent Environment Heuristics).

Knowledge about Coincided Assumptions of the Inconsistent Environments

During diagnostics of faulty devices as a result of confirmations and refutations of some predictions there is a modification of a set of inconsistent environments *Nogood*.

In each component set from *Nogood* one or more components are broken what was a reason of including a supporting set into the inconsistent environments *Nogood*. Taking the intersection of all sets of the inconsistent environments, we receive a set of components which enter into each of them, so their fault can be a reason explaining an inconsistence of each set holding in *Nogood*. Thus, we obtain the list of components a state of which is recommended to test first of all, i.e. the most probable candidates on faultiness.

The set intersection of inconsistent environments is expressed by the following equation:

$$SingleNogood = \bigcap_{E_i \in Nogood} E_i$$

If $SingleNogood = \varnothing$, it means that there are some disconnected faults. In this case the given approach is inapplicable and it is necessary to define more precisely the further information by any other methods.

After obtaining a set $SingleNogood \neq \varnothing$, on the basis of environments of value predictions in device points it is necessary to select those measurement points that allow to effectively test components to be faulted from *SingleNogood*.

For this purpose we will work with the sets obtained as a result of an intersection of each environment from *Envs(x)* with *SingleNogood:*

$Envs(x) \cap SingleNogood = \{J \cap SingleNogood : J \in Envs\{x\}\}$

The following versions are possible:

a) $\exists\ J \in Envs(x): J \equiv SingleNogood$. One of environments of the value prediction in the point x coincides with the set *SingleNogood*. The given version allows to test faulty components from the set *SingleNogood* most effectively so this measurement point *x* is selected with the most priority.

b) $\exists\ J \in Envs(x): |J \cap SingleNogood| < |SingleNogood|$. The cardinality of SingleNogood is more than the cardinality of a set obtaining as result of an intersection *SingleNogood* with a set from *Envs(x)*. We evaluate this version as $\max\limits_{J \in Envs(x)} |J \cap SingleNogood|$ i.e. the more of components from *SingleNogood* are intersected with any environment from *Envs(x)*, the more priority of a choice of the given measurement point for the observation.

c) $\exists\ J \in Envs(x): SingleNogood \subset J$. The *SingleNogood* includes in a set from *Envs(x)*. We evaluate this version as $\min\limits_{J \in Envs(x)} (|J| - |SingleNogood|)$ i.e. the less a difference between *SingleNogood* and *Envs(x),* the more priority of a choice of the given measurement point for the current observation.

d) $\forall J \in Envs(x)$: $J \cap SingleNogood = \varnothing$, i.e. no-one of the most probable faulty candidates includes in environments *Envs(x)* supporting predictions at the point x. We evaluate this version as the least priority choice, i.e. 0 in the numerical equivalent.

Also to the version (d) there are referred other methods of definition of current measurement point priorities which happen when $SingleNogood = \varnothing$. Thus in the estimations of a choice priority a numerical value returned as a result of call of other method is accepted. We call it by *ResultD(x).*

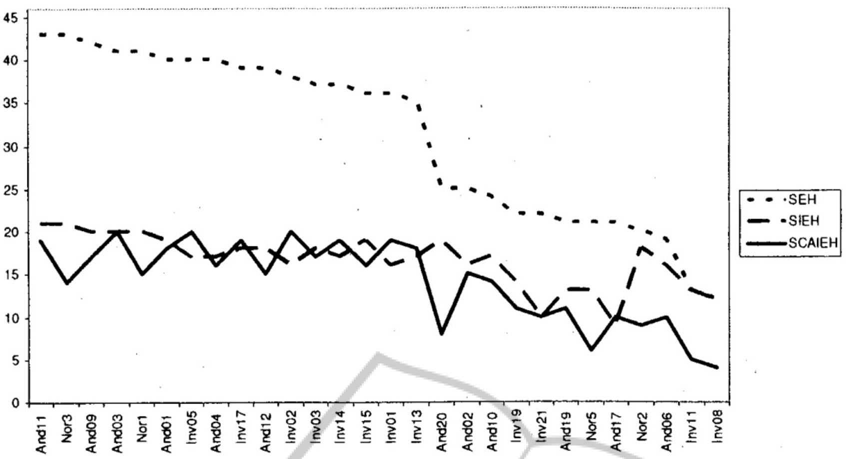

Figure 1: The quantity of stages required to each method for fault localization.

At appearance of the greater priority choosing between versions (b) and (c), heuristically we accept the version (b) as at this choice the refinement of faulty candidates is produced better.

Note for various supporting sets of the same *Envs*(*x*), the availability both the version (b) and the version (c) is also possible. In this case, as a resulting estimation for the given *Envs*(*x*) the version (b) is also accepted.

Let's estimate the obtained results.

Designate by *maxd* the maximal numerical value among versions (d) for all assessed measurement points, and by *CompCount* a quantity of device components.

Accept in reviewing the following assessments:

1. $\max_{J\in Envs(x)} |J \cap SingleNogood| < CompCount.$The quantity of components which are the intersection result is always less than the quantity of whole device components;

2. $\min_{J\in Envs(x)} (|J| - |SingleNogood|) < CompCount.$ The quantity of components in the prediction environment is always less than the quantity of the device components.

Taking into account these assessments, one can introduce a numerical assessment of the obtained results:

$$QuanSNG(x) = \begin{cases} 0, \text{ if } \forall J \in Envs(x) : J \cap SingleNogood = \varnothing \\ ResultD(x), \text{ if } SingleNogood = \varnothing \\ maxD + CompCount - \min\limits_{J\in Envs(x)} (|J| - |SingleNogood|), \\ \quad \text{if } \exists J \in Envs(x) : SingleNogood \subset J \\ maxD + CompCount + \max |J \cap SingleNogood|, \\ \quad \text{if } \exists J \in Envs(x) : |J \cap SingleNogood| < |SingleNogood| \\ maxD + 2 * CompCount, \text{ if } \exists J \in Envs(x) : J \equiv SingleNogood \end{cases}$$

The points with the greatest value of function *QuanSNG*(*x*) have the greatest priority of choice. We will call the given method as SCAIEH (Supporting and Coinciding Assumptions of Inconsistent Environment Heuristics).

The developed methods of heuristic choice of the best current measurement point are recommended to use for devices with a great quantity of components as quality of guidelines directly depends on the quantitative difference of environments.

5 PRACTICAL RESULTS

Let's test the developed methods of the best measurement point choosing for the 9-bit parity checker (Frohlich, 1998).

For each experiment one of device components is supposed working incorrectly what is exhibited in a value on its output opposite predicted. A consequence of the incorrect component work is changing of outputs of those components which produce the results depending on values on the output of a faulty component. These changed results of component operations are transmitted to appropriate inquiries of a diagnostic system.

In the beginning of each experiment to inputs of components (Invl, Inv2, Inv3, Inv7, Inv8, Inv9, Invl3, InvI4, Invl5) in a diagnostic complex the vector of values (1,0,1, 0,1,0, 1,0,1) enters. Then to the diagnostic system the value 0 retrieved from the output of the component Nor5 that depends on the work of a broken component and differs from predicted is transferred. It leads to the appearance of an inconsistency in the diagnostic system and starts the automatic process of testing.

In fig. 1 the quantity of the stages required to each method for fault localization is shown. A method stage is a measurement point choosing. The smaller the quantity of method stages, the faster a fault is localized.

From the obtained results one can see that the method efficiency for different fault components is various and hardly depends on the device structure.

Let's estimate the method efficiency. The device is consists of 46 components. The output values of 45 components are unknown (a value on the output of Nor5 is transmitted to the diagnostic system with input data together). So, the maximal stage quantity necessary for a fault definition is equal 45. Let's accept 45 stages as 100 %. For each experiment it is computed on how many percents each of the developed methods is more effective than exhaustive search of all values. Then define the average value of results. The evaluated results are represented in table 1.

Table 1: Results of experiments.

The method	SEH	SIEH	SCAIEH
On how many percents the method is more effective, %	30,79	63,17	68,65

From table 1 one can see that the greatest efficiency of current measurement point choosing has the heuristic method based on the knowledge about coincided assumptions of the inconsistent environments SCAIEH.

6 REASONING BY ANALOGY

Nowdays there are a great number of various models, schemes, and methods that describe mechanisms of ***reasoning by analogy*** (Haraguchi et al., 1986; Long et al., 1994; Varshavskii et al., 2005; Eremeev et al., 2005, 2009).

In Intelligent Systems, two types of analogies - *an analogy for solving problems and an analogy for forecasting* - are usually used:

- *The analogy for solving problems* assumes the application of reasoning by analogy for increasing the efficiency of the problem solution which, generally speaking, can be solved without analogy as well as e.g., in programming and proving theorems;
- *The analogy for prediction (forecasting)* uses reasoning by analogy for obtaining new facts. Due to the transformation of knowledge based on the likeness of objects, one can make the conclusion that new facts probably hold.

Depending on the nature of information transferred from an object of analogy to the other one, *the analogy of properties and the analogy of relations can be distinguished:*

- *The analogy of properties* considers two single objects or a pair of sets (classes) of homogeneous objects, and the transferred attributes are the properties of these objects, for example, analogy between illness symptoms of two persons or analogy in the structure of the surfaces of Earth and Mars, etc.;
- *The analogy of relations* considers pairs of objects where the objects can be absolutely different and the transferred attributes are properties of these relations. For example, using the analogy of relations, bionics studies processes in nature in order to use the obtained knowledge in a modern technology.

We consider the methods of solution search on the basis of structural analogy which allows to take into account a context and based on the theory of structural mapping. We use semantic networks as a model of knowledge representation.

Reasoning by structural analogy taking into account the context (Varshavskii et al., 2005).

Consider an ***analogy*** as a quadruple ***A* = <*O*, *C*, *R*, *p*>**, where ***O*** and ***R*** are the source object and the receiver object and ***C*** is the intersection object, i.e., the object that structurally is intersected with the source object and receiver object, and has a larger cardinality of the set of properties in the comparison with these objects. In other words, the analogy between the source object and receiver object is considered in the context of the intersection ***C***, and ***p*** is a property for the definition of an original context.

We use semantic networks (SNs) as a model of the knowledge representation for reasoning by analogy. The choice of an SN for the knowledge representation possesses an important advantage, which distinguishes it from other models, such as natural representation of structural information and fairly simple updating in a relatively homogenous environment. The latter property is very important for real-time IDSS oriented towards open and dynamical problem domains.

A semantic network is a graph **<*V*, *E*>** with labeled nodes and arcs, where ***V*** and ***E*** are sets of nodes and arcs, respectively. The nodes can represent objects (concepts, events, actions, etc.) of a problem domain, and the arcs represent relations between them.

By $\boldsymbol{Pv}$, we denote the set of properties of an object $v \in V$.

Objects $\boldsymbol{v}$, $\boldsymbol{v'} \in \boldsymbol{V}$ ***intersect*** each other on SN if and only if $Pvv' = Pv \cap Pv' \neq \varnothing$, where Pvv' is a set of common properties of objects v and v'.

By $\boldsymbol{Vp}$, we denote a set of SN objects that have a property $\boldsymbol{p}$.

By $\boldsymbol{Vv}$, $\boldsymbol{Vv} \subseteq \boldsymbol{V}$, we denote an object set of objects that intersect $\boldsymbol{v} \in \boldsymbol{V}$.

The object $\boldsymbol{C}$ is ***an intersection for A*** if and only if there is $(C\in V)$ & $(p\in PC)$ & $(nR\le nC)$ & $\neg(nR \ll nC)$ & $(nRC<nR)$ & $(nRC>1)$, where nR and nC are the numbers of properties of the receiver R and the intersection C, respectively; nRC is the number of their common properties, $\neg(nR \ll nC)$ denotes that receiver R should not be much smaller than intersection C (i.e., the possibility of absorbing the receiver R by the intersection C, since, here, the probability of receiving a false analogy increases).

The object $\boldsymbol{O}$ is ***the source for analogy A*** if and only if there is $(O\in V)$ & $(p\in PO)$ & $(nO\le nC)$ & $\neg(nO \ll nC)$ & $(nOC<nO)$ & $(nOC>1)$, where nO is the number of properties of the source O; nOC is the number of common properties of the source O and intersection C; and other notations are analogous to the previous definition.

By $\boldsymbol{VC}$, $\boldsymbol{VC} \subseteq \boldsymbol{Vp}$, we denote the set of objects that are candidates for the role of intersection C for analogy A.

By $\boldsymbol{VO} \subseteq \boldsymbol{Vp}$, we denote the set of objects that are candidates for the role of source O for analogy A.

By $\boldsymbol{VA}$, we denote the set of analogies A.

The set $\boldsymbol{POCR} = \boldsymbol{PO} \cap \boldsymbol{PC} \cap \boldsymbol{PR}$ denotes ***the context***, with respect to which analogy $\boldsymbol{A}$ is considered.

We consider the structure of the SN in detail (for Metalevel and for Situation 1) using the example from power engineering - operation control of the nuclear power unit (fig. 2) (Eremeev et al., 2006a).

Let us give a semantic interpretation of the information given in the SN for Situation 1:

- It is recommended to supply the pump TH11D01 with boric concentrate 40g/kg caused by switching off automatic cooling system ACS 1 due to closing the gates TH11S24 and TH11S25;
- ACS 2 is switched off due to the closed gates TH12S24 and TH12S25;
- The upper setting T517B01 is equal to 63;
- The lower setting T517B01 is equal to 56;
- The upper setting TH11T500 is equal to 60;
- The lower setting TH11T500 is equal to 20.

Analogously, the SNs for Situations 2,3 which are structurally close to Situation 1 are built.

Algorithm of reasoning by structural analogy

An SN with information about the problem domain, a receiver R, and the property for defining the original context $\boldsymbol{p}$ provide input data for this algorithm.

The algorithm for the problem solution on the basis of analogy taking into account the context consists of the following steps:

Step 1. $\boldsymbol{VC} = \varnothing$, $\boldsymbol{VO} = \varnothing$, $\boldsymbol{VA} = \varnothing$. Determine all objects of the SN, except for receiver $\boldsymbol{R}$, that have property $\boldsymbol{p}$ ($\boldsymbol{Vp'} = \boldsymbol{Vp} \setminus \{\boldsymbol{R}\}$). If there are no objects of this kind, then the search for a solution fails (without finding an analogy), otherwise, go to **step 2**.

Step 2. For the objects found in step 1, determine all possible intersections of $\boldsymbol{C}$ with $\boldsymbol{R}$ taking into account $\boldsymbol{p}$ ($\boldsymbol{VC}$). If there are no intersections of C with R ($\boldsymbol{VC} = \varnothing$), the first search for a solution fails, otherwise, go to step 3.

Step 3. From the objects extracted in step 1, determine all possible sources $\boldsymbol{O}$ for analogies ($\boldsymbol{VO}$). In the case of success ($\boldsymbol{VO} \neq \varnothing$), go to step 4, otherwise, the search for a solution fails.

Step 4. Construct possible analogies for $\boldsymbol{R}$ using the sets $\boldsymbol{VC}$ and $\boldsymbol{VO}$. Add new analogy $\boldsymbol{A} = \langle \boldsymbol{O}, \boldsymbol{C}, \boldsymbol{R}, \boldsymbol{p} \rangle$ to $\boldsymbol{VA}$ if and only if there exists an analogy $\boldsymbol{A'} = \langle \boldsymbol{O'}, \boldsymbol{C}, \boldsymbol{R}, \boldsymbol{p} \rangle$, $\boldsymbol{O} \neq \boldsymbol{O'}$. In the case of success ($\boldsymbol{VA} \neq \varnothing$), go to step 5; otherwise, the search for a solution fails.

Step 5. The analogies obtained in step 4 ($\boldsymbol{VA}$) (which could be previously compared with each other taking into account the context) are given to the decision making person (DMP), which means successful termination of the algorithm.

Having obtained analogies, the DMP may then make the final choice of the best ones. On the basis of these facts, the facts (properties) that hold for the source O are transferred to the receiver R.

Let us consider the steps of the functioning of the algorithm using the example from power engineering - operation control of the nuclear power unit.

As a receiver R for the analogy, we take Situation 4 (see fig. 3) and as the property p, we take Close TH11S24.

In the first step, $VC = \varnothing$, $VO = \varnothing$, $VA = \varnothing$ and Vp' = {Situation 1, Situation 2, Situation 3}. Since $Vp' \neq \varnothing$, we go to the next step.

Determine intersections of C with R taking into account p. Add in VC only Situation 1, because the number of common properties $nRC = nR$ for

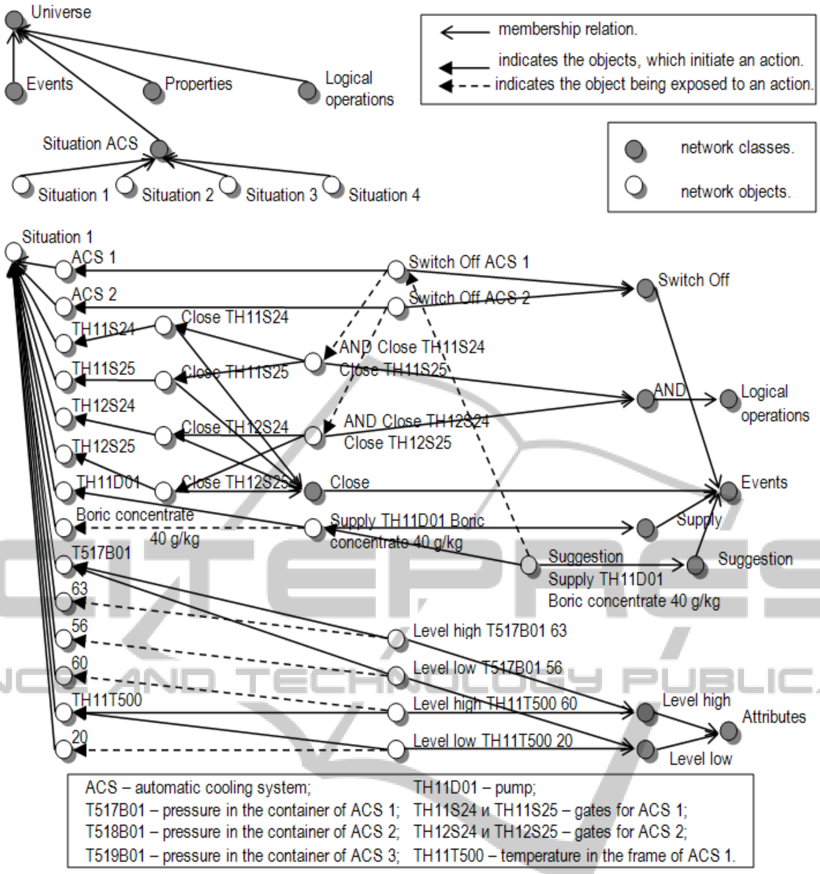

Figure 2: A fragment of the SN that represents the Metalevel and the Situation 1 that was formed in the course of ACS functioning.

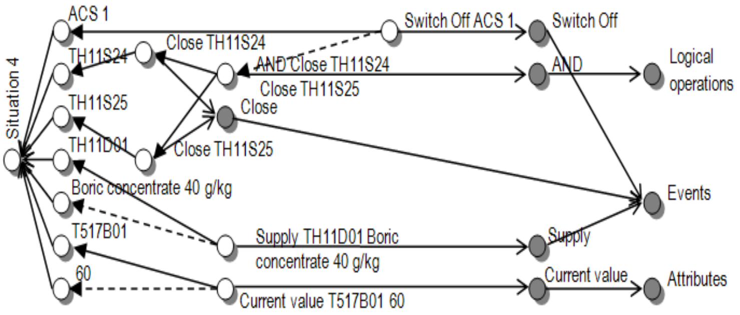

Figure 3: A fragment of the SN that represents the Situation 4.

Situation 2 and Situation 3. Since $VC \neq \varnothing$, we go to the step 3.

Determine all possible sources O and go to step 4. In this case VO = {Situation 2, Situation 3}, because the Situation 1 is unique intersection for analogy.

In the fourth step, we construct only two analogies for R - Situation 4:

***A1* = <Situation *2*, Situation *1*, Situation *4*, Close TH11S24 >;**

***A2* = <Situation *3*, Situation *1*, Situation *4*, Close TH11S24 >.**

Add new analogies to ***VA*** and go to step 5.

The analogies obtained in step 4 (*A1, A2*) are given to the DMP.

As a result we obtain two analogies. Choosing one of them, the DMP can transfer facts that hold for the source of the analogy to its receiver. In this example, a new fact about the recommendation ***"Supply the pump TH11D01 with boric concentrate 40g/kg caused by switching off ACS 1 due to closing the gates TH11S24 and TH11S25"*** arises for Situation 4.

The methods of reasoning by analogy is more general than on the bases of cases. Analogies are used when it is impossible to find a suitable case in a case library. The reasoning by analogy method can be used independently from a case- based reasoning method as well as for correction (adaptation) of the nearest to a problem situation case to form a new case for completing a case library. Further we shall consider the case-based reasoning method and its application.

7 CONCLUSIONS

The heuristic methods of finding the best current measurement point based on environments of device components work predictions are presented.

Practical experiments have confirmed the greatest efficiency of current measurement point choosing for the heuristic method based on the knowledge about coincided assumptions of the inconsistent environments SCAIEH.

Advantages of heuristic methods of the best current measurement point choosing is the simplicity of evaluations and lack of necessity to take into consideration the internal structure interconnections between components of the device.

The method of reasoning by analogy on the basis of structural analogy was considered from the aspect of its application in modern intelligent systems, in particular, for a solution of problems of real-time diagnostics and forecasting . The example of the algorithm for solution search on the basis of analogy of properties that takes into account the context was proposed. This algorithm uses a modified structure of analogy that is capable of taking into account not one property (as in the base algorithm), but a set of properties. These properties determine the original context of analogy and transfer from the source to the receiver only those facts that are relevant in the context of the constructed analogy.

The presented methods and tools were applied at implementation of a prototype of Intelligent Diagnosis System on the basis of non-classical logics for monitoring and control of complex objects like power units and electronic circuits (Eremeev et al., 2007, 2009).

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