Computer Communication & Collaboration (Vol. 2, Issue 1, 2014)
Submitted on 16/October/2013
DOIC: 2292-1036-2014-01-002-20

Automated Planning with the Aid of Case-based Reasoning and Group Decision-making Methods[1]

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Abstract: The paper describes an approach for automated planning and scheduling based on cases and group decision-making methods. The proposed approach can be considered a new method of transformational adaptation in the context of planning. In planning, cases contain the solutions (as plans) for previous problems in the form of a completely or partially ordered sequence of actions (parts of a solution). Transformation operators transform existing plans into new ones that are reused in new situations. In the proposed approach the order of solution parts is determined with the aid of strictly formalised decision-making methods using proven mathematical methods of decision theory and corresponds to the «group preferences relation» concept of decision theory, i.e., it has the property transitivity.

Keywords: Adaptation, Case-based reasoning, Group decision-making, Planning

1. Introduction

One of the important problems in many subject domains (including automated planning) is the problem of improving experience reuse efficiency in solving new problems. Case-based reasoning [1-3] is one approach to solving this problem. This approach uses (or simulates) a human reasoning model in decision-making by analogy and does not require deep analysis of a subject domain. An effective application of this approach can be made on the basis of superficial knowledge represented in the form of structured patterns or cases.

Case-based decision-making as a separate scientific area in the field of knowledge-based systems is oriented primarily toward decision-making through the reuse of experience. This orientation requires investigation into and development of effective new methods for representation (modelling), evaluation, storage, indexing, retrieval and adaptation of actual knowledge. In accordance with this methodology, the decision-making process as a rule consists of four stages [1-3]:

- Retrieval of similar cases, including recognition of a new problem presented in the form of a pattern (a case);

[1] The research is partially funded by the grant № 2012-1.2.2-12-000-2007-027 of the Federal Program "Scientific and Scientific-Pedagogical Staff of Innovative Russia" and the grant № 2012.2012.5 of the President of Russian Federation.

- Reuse of information from retrieved cases, including its adaptation (if necessary);

- Revision of a new solution for correctness; and

- Retaining a new case in a case-base.

The reuse stage is the most complex because it utilises deep subject-domain knowledge. This knowledge allows us to estimate qualitative differences between retrieved cases and the new problem and to take into account these differences in the formation of the final solution, i.e., to adapt the solutions received.

The problem of developing adaptation methods has remained constant since the early investigations into case-based reasoning [4-7]. Case adaptation methods can be classified [1,2,8-10] into two basic categories: transformational analogy and derivational analogy.

In transformational analogy, case solutions are reused in new situations by making appropriate changes, if necessary with the aid of transformation operators. Transformational analogy does not consider how the reused solution was originally obtained; it is only concerned with the solution itself. In derivational analogy [11], solutions contain derivational traces that can be replayed relative to the new problem (and do not require transformational operators). However, derivational analogy requires the derivational trace to be known. When this is not possible, transformational analogy is the better choice because the solution itself can be used for adaptation.

This paper describes an approach that can be considered a method of transformational adaptation in the context of planning [8,10,12]. In planning, cases contain solution plans for previous problems in the form of a completely or partially ordered sequence of actions. These plans are reused in the new situation by making suitable changes where appropriate. Transformation operators transform existing plans into new ones.

We propose implementing the transformation operator on the basis of group decision-making (GDM) methods [13,14]. The final solution is the result of aggregating multiple solutions of similar cases rather than a single best-case solution. Parts of solutions coming from different retrieved cases are combined together in the process of aggregation. An ordered sequence of parts corresponds to the concept «group preference relation» [13] of decision theory.

2. Problem Statement

One feature of case-based reasoning [1,2] is to obtain a set of similar cases from the case retrieval stage. The cases are ordered according to their similarity, and a decision-maker creates a solution for the new situation on the basis of one or more similar cases. In the context of planning, the solution is a plan in the form of a sequence of actions ordered by priority or acceptance time. Thus, a decision-making process (in particular, a procedure combining parts of solutions of similar cases) can be improved with the aid of GDM methods [13-15].

The use of GDM methods provides for obtaining the solution by aggregating solutions from similar cases, even those that are usually excluded from a decision-making process.

Consider a formal statement of the problem.

It is given: $C = \{c_1, \mathbf{K}, c_M\}$ is a set of retrieved cases, and each case is described by the triple: $c_i = \langle p_i, d_i, s_i \rangle$, where p_i is an *i*-case description, d_i is an *i*-case solution, and s_i is an *i*-case similarity, $i \in \overline{1, M}$.

Consider the situation where case solution d_i is a set (or a sequence) of alternatives (events, actions) ordered by decision time, then $d_i = \left\langle A_i^c, d_i^Q \right\rangle$ where $A_i^c = \left\{a_{i1}^{h_1}, \ldots, a_{iZ_i}^{h_{Z_i}}\right\}$ is the set of alternatives (events, actions), and $A_i^c \cap A_j^c \neq \varnothing$. The union of sets A_i^c forms a set of all possible alternatives for A for C : $A = \bigcup_{i=1}^{M} A_i^c = \left\{a^1, \ldots, a^H\right\}$, $H = |A|$, and $h_z \in \overline{1,H}$. $d_i^Q = a_{i1}^{h_1} Q_1^i \ldots Q_{Z_i-1}^i a_{iZ_i}^{h_{Z_i}}$ is the sequence of alternatives (or ranking), where $Q \in \{\succ, \approx\}$, i.e., Q is a relation of strict preference ($\succ$) or equivalence ($\approx$) [13], $Z_i = \left|A_i^c\right|$, and c is an index of affiliation of alternatives to cases. Thus, it is possible that $A_i^c = A_j^c$, but $d_i^Q \neq d_j^Q$, $i, j \in \overline{1,M}$.

We must obtain the solution d^* by aggregating the solutions of cases from C and taking into account their similarities.

The solution d^* corresponds to the concept «group preference relation». The preference relation is a formal description of an expert's ability to compare (or to order) different alternatives in the set A. The preference relation can be described quantitatively (by units of measurement) or qualitatively (using the expert's subjective opinion). The preference relation in this work is described qualitatively, and the relations of strict preference ($\succ$) and equivalence ($\approx$) are used. The equivalence relation ($\approx$) is a binary relation on the set A that satisfies the following conditions:

- reflexivity: $\forall a^i \in A,\ i \in H:\ a^i \approx a^i$;

- symmetry: if $a^i \approx a^j$ then $a^j \approx a^i$, $\forall a^i, a^j \in A,\ i, j \in H$; and

- transitivity: if $a^i \approx a^j$ and $a^j \approx a^k$ then $a^i \approx a^k$, $\forall a^i, a^j, a^k \in A,\ i, j, k \in H$.

The strict preference relation ($\succ$) is a binary relation on the set A that satisfies the following conditions:

- irreflexivity: $\neg \exists a^i \in A,\ i \in H;\ a^i \succ a^i$;

- transitivity: $a^i \succ a^j \wedge a^j \succ a^k \Rightarrow a^i \succ a^k$; $a^i \approx a^j \wedge a^j \succ a^k \Rightarrow a^i \succ a^k$; and $a^i \succ a^j \wedge a^j \approx a^k \Rightarrow a^i \succ a^k$, $a^i \approx a^k$, $\forall a^i, a^j, a^k \in A,\ i, j, k \in H$.

Thus, the group preference relation is a formal consensus of experts working in a group, and each of them has an individual preference relation.

3. Proposed Approach

The proposed approach allows us to represent information on the solutions of retrieved cases in the form of datasets. The obtained datasets are processed by several GDM methods with the following coordination (or aggregation) of results. The basic scheme of the proposed approach is presented in Fig. 1.

The generalised algorithm of the proposed approach consists of the following steps:

Step 1: Case selection for forming datasets;

Step 2: Dataset formation for processing by GDM methods**;**

Step 3: Dataset processing by GDM methods; and

Step 4. Obtaining a final aggregated solution by the coordination (or aggregation) of intermediate solutions obtained in Step 3.

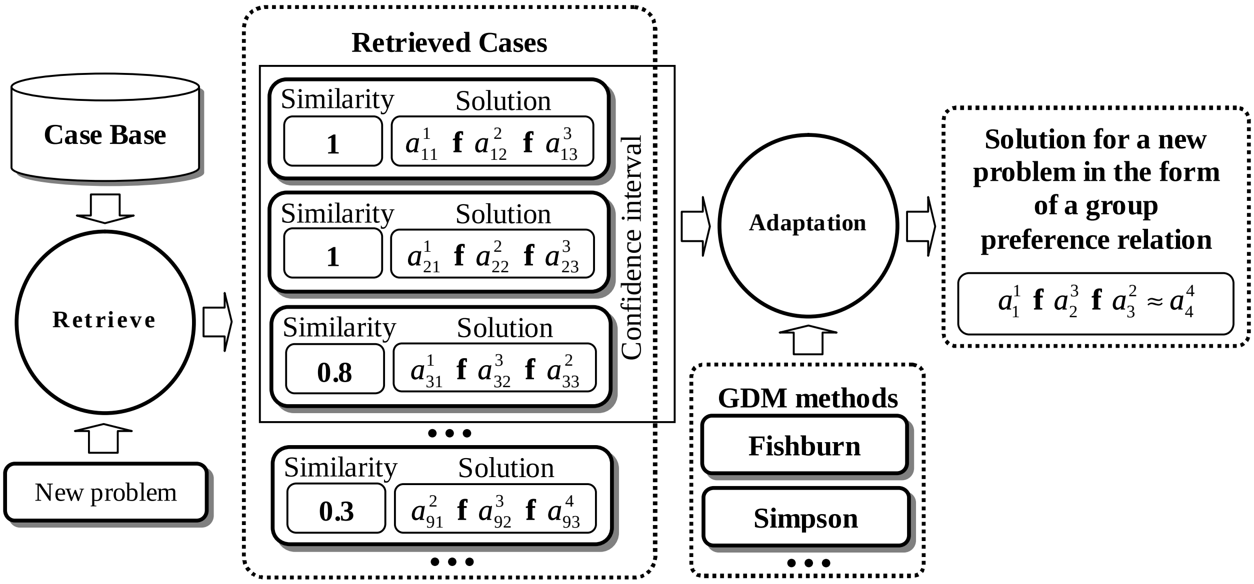

Fig. 1: The basic scheme of the proposed approach

Let us consider the steps of the algorithm in detail.

Step 1: Case selection is based on the results of the case-retrieval procedure. There are many methods and modifications that can be used for case retrieval [1-3]: nearest neighbour, decision trees, etc. The most popular method is the nearest neighbour, based on an assessment of similarity with the aid of different metrics, for example, Euclidean, City-Block-Metric, etc. The proposed approach uses the nearest neighbour method and Zhuravlev metric [16] with normalisation:

$$d_G(\bar{x},\bar{y}) = \sum_{i=1}^{N} w_i h_G(x_i, y_i) \Big/ N, \quad h_G(x_i, y_i) = \begin{cases} \text{for quantitative} \begin{cases} 1, if\,|x_i - y_i| < x \\ 0, else \end{cases} \\ \text{for qualitative} \begin{cases} 1, x_i = y_i \\ 0, x_i \neq y_i \end{cases} \end{cases},$$

where w_i is the information weight, and x is the constraint on the difference between the values of properties.

At the same time, the normalisation (or standardisation) procedure is performed to bring all values onto a single scale:

$$x_{ik} \to \left(x_{ik} - \min_k x_{ik} \right) \Big/ \left(\max_k x_{ik} - \min_k x_{ik} \right).$$

In most cases, case selection (to obtain a final solution for the new problem) is a subjective process. That is why the implementation of this approach in [17] allows the user to determine the confidence interval for similarity to select the cases. In this illustrative example (see below), cases with similarity greater than or equal to 0.5 were selected (the confidence interval is [0.5, 1]).

The result of Step 1 is the set of cases $C^* = \{c_1, \ldots, c_m\}$, where $c_i = \langle p_i, d_i, s_i \rangle, i = \overline{1, m}$, $m \le M$, $s_i \in [0.5;1]$, $d_i = \langle A_i^c, d_i^Q \rangle$, $A_i^c = \{a_i^{h_1}, \ldots, a_{iZ_i}^{h_{Z_i}}\}$, and $d_i^Q = a_{i1}^{h_1} Q_1^i \ldots Q_{Z_i-1}^i a_{iZ_i}^{h_{Z_i}}$.

Step 2. Dataset formation: *T* on the basis of information from cases that are selected in Step 1. In this step, the following tasks are solved:

2.1. Grouping cases by taking into account alternatives to their solutions; and

2.2. Taking into account the similarity of cases at dataset formation.

The first task is solved as follows: the set of cases C^* selected in Step 1 is divided into disjoint subsets $\overline{C}_n$, $C^* = \bigcup_{n=1}^{q} \overline{C}_n, q \le m,\ \overline{C}_{n1} \cap \overline{C}_{n2} = \varnothing$, and $n1 \ne n2, \forall n1, n2 \in \overline{1, q}$, each of which represents a set of cases $\overline{C}_n = \{c_{n1}, \ldots, c_{nK_n}\}, n = \overline{1, q}$. In addition, each subset $\overline{C}_n$ has a unique set of alternatives, i.e., sets of alternatives are equal for cases from one subset: $\forall c_{nk1}, c_{nk2} \in \overline{C}_n : A_{nk1}^c = A_{nk2}^c, k1 \ne k2$; and $k1, k2 \in \overline{1, K_n}$, and sets of alternatives are different for cases from different subsets: $\forall c_{n1k1} \in \overline{C}_{n1}, \forall c_{n2k2} \in \overline{C}_{n2} : A_{n1k1}^c \ne A_{nk2}^c$; $n1 \ne n2$; $n1, n2 \in \overline{1, q}$; $k1 \ne k2$; and $k1, k2 \in \overline{1, K_n}$. The dataset is formed for each subset $\overline{C}_n \to T_n$, $n = \overline{1, q}$, so the result of Step 2 is the set of datasets $T = \{T_1, \ldots, T_q\}$.

Let us describe components of the dataset $T_n = \langle A_n^T, R_n, S_n \rangle$, $n = \overline{1, q}, q \ge 1$, where A_n^T is a set of alternatives to the dataset: $A_n^T = \{a_{n1}^{h_1}, \ldots, a_{nL_n}^{h_{L_n}}\}$, L_n is a number of alternatives in the dataset, and R_n is a set of rankings (or sequences of alternatives), $R_n = \{\langle d_{n1}^Q, e_{n1} \rangle, \langle d_{n2}^Q, e_{n2} \rangle, \ldots, \langle d_{nr}^Q, e_{nr} \rangle\}$, where r is a number of unique solutions (rankings), $r \le m$, and d_{nr}^Q is a case solution (represented in the form of a ranking) that is identical for a number of cases e_{nr}. S_n is an informational weight of the dataset T_n. Calculation of the informational weight allows us to solve the second task of Step 2. It is equal to the mean expression of similarities for cases of the dataset.

Thus, the components of a case are mapped into the components of a dataset: $\{A_{nk}^c\}_k \to A_n^T$, $\{d_{nk}^Q\} \to R_n$, $\{s_{nk}\} \to S_n$.

Let us consider an example illustrating the first two steps of the generalised algorithm for the proposed approach.

The set of cases *C* is given, and the cases are ordered according to their similarities:

$$c_1 = \langle p_1, d_1, s_1 \rangle,\ A_1^c = \{a_{11}^1, a_{12}^2, a_{13}^3\},\ d_1^Q = a_{11}^1 \succ a_{12}^2 \succ a_{13}^3,\ s_1 = 1.0$$

$$c_2 = \langle p_2, d_2, s_2 \rangle,\ A_2^c = \{a_{21}^1, a_{22}^2, a_{23}^3\},\ d_2^Q = a_{21}^1 \succ a_{22}^2 \succ a_{23}^3, s_2 = 1.0$$

$$c_3 = \langle p_3, d_3, s_3 \rangle,\ A_3^c = \{a_{31}^1, a_{32}^3, a_{33}^2\},\ d_3^Q = a_{31}^1 \succ a_{32}^3 \succ a_{33}^2, s_3 = 0.8$$

$$c_4 = \langle p_4, d_4, s_4 \rangle,\ A_4^c = \{a_{41}^1, a_{42}^3, a_{43}^4\},\ d_4^Q = a_{41}^1 \succ a_{42}^3 \succ a_{43}^4, s_4 = 0.7$$

$$c_5 = \langle p_5, d_5, s_5 \rangle,\ A_5^c = \{a_{51}^1, a_{52}^3, a_{53}^4\},\ d_5^Q = a_{51}^1 \succ a_{52}^3 \succ a_{53}^4,\ s_5 = 0.6$$

$$c_6 = \langle p_6, d_6, s_6 \rangle,\ A_6^c = \{a_{61}^3, a_{62}^4\},\ d_6^Q = a_{61}^3 \succ a_{62}^4, s_6 = 0.6$$

$c_7 = \langle p_7, d_7, s_7 \rangle$, $A_7^c = \{a_{71}^3, a_{72}^2, a_{73}^1\}$, $d_7^Q = a_{71}^3 \mathbf{f}\ a_{72}^2 \mathbf{f}\ a_{73}^1$, $s_7 = 0.5$

$c_8 = \langle p_8, d_8, s_8 \rangle$, $A_8^c = \{a_{81}^2, a_{82}^3, a_{83}^1\}$, $d_8^Q = a_{81}^2 \mathbf{f}\ a_{82}^3 \mathbf{f}\ a_{83}^1$, $s_8 = 0.5$

$c_9 = \langle p_9, d_9, s_9 \rangle$, …, $s_9 = 0.3$

$c_{10} = \langle p_{10}, d_{10}, s_{10} \rangle$, …, $s_{10} = 0.1$

$c_{11} = \langle p_{11}, d_{11}, s_{11} \rangle$, …, $s_{11} = 0.0$

…

$A = \{a^1, a^2, a^3, a^4\}$ is a set of possible alternatives.

The set $C^* = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8\}$ is obtained from the selection of cases with similarities greater than or equal to 0.5 (Step 1). Three subsets of cases are formed as a result of the analysis of C^* (Step 2, Task 2.1): $C^* = \{\overline{C}_1, \overline{C}_2, \overline{C}_3\}$, $\overline{C}_1 = \{c_1, c_2, c_3, c_7, c_8\}$, $\overline{C}_2 = \{c_4, c_5\}$, and $\overline{C}_3 = \{c_6\}$. The set of datasets $T = \{T_1, T_2, T_3\}$ is obtained on the basis of these subsets (Step 2):

$T_1 = \langle A_1^T, R_1, S_1 \rangle$: $A_1^T = \{a_{11}^1, a_{12}^2, a_{13}^3\}$, $R_1 = \{\langle d_{11}^Q, 2\rangle, \langle d_{12}^Q, 1\rangle, \langle d_{13}^Q, 1\rangle, \langle d_{14}^Q, 1\rangle\}$, $d_{11}^Q = a_{111}^1 \mathbf{f}\ a_{112}^2 \mathbf{f}\ a_{113}^3$, $d_{12}^Q = a_{121}^1 \mathbf{f}\ a_{122}^3 \mathbf{f}\ a_{123}^2$, $d_{13}^Q = a_{131}^3 \mathbf{f}\ a_{132}^2 \mathbf{f}\ a_{133}^1$, $d_{14}^Q = a_{141}^2 \mathbf{f}\ a_{142}^3 \mathbf{f}\ a_{143}^1, S_1 = 0.76$;

$T_2 = \langle A_2^T, R_2, S_2 \rangle$: $A_2^T = \{a_{21}^1, a_{22}^3, a_{23}^4\}$, $R_2 = \{\langle d_{21}^Q, 2\rangle\}$, $d_{21}^Q = a_{211}^1 \mathbf{f}\ a_{212}^3 \mathbf{f}\ a_{213}^4, S_2 = 0.65$; and

$T_3 = \langle A_3^T, R_3, S_3 \rangle$: $A_3^T = \{a_{31}^3, a_{32}^4\}$, $R_3 = \{\langle d_{31}^Q, 1\rangle\}$, $d_{31}^Q = a_{311}^3 \mathbf{f}\ a_{312}^4$, $S_3 = 0.6$.

Step 3: Processing datasets from T by GDM methods

Thus, the set of datasets $T = \{T_1, \mathbf{K}, T_q\}$ is obtained in Step 2.

We must obtain the set of solutions $D = \{d_1^*, \mathbf{K}, d_q^*\}$ for T where $d_n^* = a_{n1}^{h_1} Q_1^n \ldots Q_{l-1}^n a_{nL_n}^{h_{L_n}}$ is a group preference relation represented in the form of a ranking.

The efficiency of dataset processing can be improved as follows:

- by processing each dataset with the aid of several GDM methods in coordination with the results. We assume that the application of several GDM methods reduces the probability of incorrect solutions and paradoxes;

- by applying an algorithm of the results' sequential coordination. This algorithm allows us to gradually obtain a solution in two stages. A certain set of GDM methods operates at the first stage, and its results are group preference relations (method selection also depends on the user's subjective preferences). Further, the results of the first stage are used as the input for the second stage, which uses only one GDM method. This algorithm provides a solution that does not depend on the features (or restrictions) of the various GDM methods.

The result of Step 3 is the set of intermediate solutions $D = \{d_1^*, \ldots, d_q^*\}$.

Step 4. Obtaining a final aggregated solution. The purpose of this step is to obtain the aggregated solution d^* by coordinating (or aggregating) the intermediate solutions from D. This step can be omitted if $|D| = 1$; otherwise, we must form the dataset T^* on the basis of D and process it with the aid of GDM methods. Thus, the intermediate solutions $d_n^*, n \in \overline{1,q}$ should be complemented by alternatives from A to form generalised rankings in R^* of identical capacity. All complemented alternatives are equivalent to each other.

The result of Step 4 is the final aggregate solution d^*.

Let us explain Step 4 in this example. The following intermediate solutions for $T = \{T_1, T_2, T_3\}$ are obtained in Step 3: $d_1^* = a_{11}^1 \succ a_{12}^2 \succ a_{13}^3$, $d_2^* = a_{21}^1 \succ a_{22}^3 \succ a_{23}^4$, and $d_3^* = a_{31}^3 \succ a_{32}^4$.

Because $|D| = 3$ the intermediate solutions are complemented by alternatives from $A = \bigcup_{n=1}^{3} A_n^T = \{a^1, a^2, a^3, a^4\}$, and as a result a new set of rankings is obtained: $R^* = \{\langle d_1^{Q*}, e_1^* \rangle, \langle d_2^{Q*}, e_2^* \rangle, \langle d_3^{Q*}, e_3^* \rangle\}$, where $d_1^{Q*} = a_{11}^1 \succ a_{12}^2 \succ a_{13}^3 \succ a_{14}^4$, $e_1^* = 76$; $d_2^{Q*} = a_{21}^1 \succ a_{22}^3 \succ a_{23}^4 \succ a_{24}^2$, $e_2^* = 65$; and $d_3^{Q*} = a_{31}^3 \succ a_{32}^4 \succ a_{33}^1 \approx a_{34}^2$, $e_3^* = 60$. e_n^* is formed by the transformation of an informational dataset weight: $S_q \to e_q^*$, $q = \overline{1,n}$, $e_q^* = S_q * 100 \ \forall q = \overline{1,n}$. This transformation allows us to move from fractional numbers to integers that are used to describe generalised rankings.

The final result is $d^* = a_1^1 \succ a_2^3 \succ a_3^2 \approx a_4^4$.

4. Conclusion

This paper describes an approach to improving the efficiency of case-based decision support with the aid of group decision-making methods. The proposed approach can be considered a new method of transformational adaptation in the context of planning. In planning, cases contain the solutions (as plans) for previous problems in the form of a completely or partially ordered sequence of actions (parts of a solution). Transformation operators transform existing plans into new ones that are reused in new situations. In the proposed approach the transformation operator is implemented on the basis of group decision-making (GDM) methods.

The advantages of this approach:

- the transformation operator takes into account multiple solutions of the best cases;

- the order of solution parts is determined with the aid of strictly formalised decision-making methods using proven mathematical methods of decision theory; and

- the order of solution parts corresponds to the "group preferences relation" concept of decision theory, i.e., it has the property transitivity.

The limitations of this approach:

it is applicable only to planning, when solutions are ordered sequences of actions; and

the final solution is just "average", i.e., it is not always acceptable.

The practical significance of the proposed approach is determined by group decision-making–the opportunity to establish a more accurately ordered sequence by taking into account all points of view (in our case, an ordered sequence is a solution). The best and worst elements in the sequence are usually obvious, but revealing the distribution of intermediates can be difficult.

The proposed approach has been applied to case-based decision support in defining recommendations to prevent repeated failures in petro-chemistry [17,18] . In particular, a new module that implements this approach has been added to intelligent software [18], and the application of the proposed approach is described in detail in [17]. The case model includes a description of diagnostic signs of an incident or failure. These signs allow us to identify the current technical state of the object of investigation. In addition, the case model includes a list of actions (or recommendations) to prevent and reduce losses from failures. Actions (or recommendations) form a strictly ordered sequence or plan. The proposed approach expands the recommendation set to prevent repeated failures. This expansion is achieved by integrating solution elements of retrieved cases that were previously ignored.

Acknowledgments: The research is partially funded by the grant № 2012-1.2.2-12-000-2007-027 of the Federal Program "Scientific and Scientific-Pedagogical Staff of Innovative Russia" and the grant № 2012.2012.5 of the President of Russian Federation.

References

[1]. Aamodt A, Plaza E (1994). Case-based reasoning: foundational issues, methodological variations, and system approaches, *Artificial Intelligence Communications*, 7(1): 39-59.

[2]. Bergmann R (2002). Experience Management: Foundations, Development Methodology and Internet-Based Applications, LNCS. 2432: 1-393.

[3]. Lopez De Mantaras R, Mcsherry D, Bridge D, Leake D, Smyth B, Craw S, Faltings B, Maher ML, Cox MT, Forbus K, Keane M, Aamodt A, Watson I (2005). Retrieval, reuse, revision and retention in case-based reasoning, *Knowledge Engineering Review*, 20(3): 215–240.

[4]. Kolodner JL (1993). Case-Based Reasoning, Morgan Kaufmann, San Mateo, CA.

[5]. McSherry D (1998). An adaptation heuristic for case-based estimation, LNCS 1488: 184-195.

[6]. Plaza E, Arcos J L (2002). Constructive Adaptation, LNCS. 2416: 306-320.

[7]. Wilke W, Smyth B, Cunningham P (1998). Using configuration techniques for adaptation, LNCS 1400: 139-168.

[8]. Cox MT, Muñoz-Avila H, Bergmann R (2006). Case-based planning, *Knowledge Engineering Review*, 20(3): 283-287.

[9]. Mitra R, Basak J (2005). Methods of case adaptation: A survey, *International Journal of Intelligent Systems*, 20 (6): 627-645.

[10]. Muñoz-Avila H, Cox MT (2008). Case-Based Plan Adaptation: An Analysis and Review, *IEEE Intelligent Systems*, 23(4): 75-81.

[11]. Veloso MM, Carbonell JG (1993). Derivational Analogy in PRODIGY: Automating Case Acquisition, Storage, and Utilization, *Machine Learning*, 10(3): 249-278.

[12]. Britanik J, Marefat M (2004). CBPOP: A Domain-Independent Multi-Case Reuse Planner, *Computational Intelligence*, 20(2): 405-443.

[13]. Arrow K.J., Sen A.K., Suzumura K (2002). Handbook of social choice and welfare, North

Holland: Gulf Professional Publishing.

[14]. Moulin H (1998). Axioms of Cooperative Decision Making. Cambridge: Cambridge University Press.

[15]. Fishburn PC (1968). Theory of social choice. Princeton: Princeton University Press.

[16]. Zhuravlev Yu I, Gurevitch IB (1989)(Eds.) Pattern recognition and image recognition, Pattern recognition, classification, forecasting: Mathematical techniques and their application, Moscow: MAIK Nauka (in Russia).

[17]. Yurin AY (2012). An approach for definition of recommendations for prevention of repeated failures with the aid of case-based reasoning and group decision-making methods, *Expert Systems with Applications*, 39(10): 9282-9287.

[18]. Nikolaychuk OA, Yurin AY (2008). Computer-aided identification of mechanical system's technical state with the aid of case-based reasoning, *Expert Systems with Applications*, 34(1): 635-642.