Towards a General Framework for Substitutional Adaptation in Case–Based Reasoning

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Abstract. Adaptation is one of the most problematic steps in the design and development of Case Based Reasoning (CBR) systems, as it may require considerable domain knowledge and involve complex knowledge engineering tasks. This paper describes a general framework for substitutional adaptation, which only requires analogical domain knowledge, very similar to the one required to define a similarity function. The approach is formally defined, and its applicability is discussed with reference to case structure and its variability. A case study focused on the adaptation of cases related to truck tyre production processes is also presented.

1 Introduction

The acquisition of knowledge required to implement the capability of adapting the solution to a past case in a different, although similar, situation is a general issue in the development of Case Based Reasoning (CBR) systems (see, e.g., [1]). CBR approach allows to tackle problems still not well understood, in which it is not possible to build a theory or a model supporting the problem solving activity. In general, in these situations it is also difficult to develop a method to adapt the solution of the retrieved case to the case the target case that has to be solved. In particular, even if the required knowledge is actually available, it is a complex knowledge engineering task to acquire, represent and implement it into a specific adaptation module.

A taxonomy of various approaches to case adaptation can be found in [2], and two main categories of adaptation approaches are identified. *Transformational* approaches provide the modification of the solution of a retrieved case to better fit the new situation (through the *substitution* of certain solution features or even the modification of its *structure*). *Generative* adaptation schemes instead build from scratch part of the solution, according to current case description features and the description of the reasoning process that led to the solution of the retrieved best–matching case. In general, whatever adaptation approach is selected, the involved knowledge is strictly domain specific and it cannot be simply generalized.

The aim of this paper is to present a general framework for substitutional approach to adaptation which only requires and exploits *analogical* knowledge, that is, domain knowledge that is already employed by the CBR system in order to evaluate differences and similarity between cases. The underlying idea of the here presented approach considers that past cases may give an indication on how to adapt the solution of the retrieved case given the difference among its description and the one related to the current problem. The difference among current and retrieved case descriptions is used as a criteria to select from the Case Base pairs of representatives of these cases, whose solutions (and more precisely, the difference among their solutions) are aggregated to define the way to adapt the solution of the retrieved case to solve the current one.

The following Section introduces the context of this work and describes other adaptation approaches that can be found in the literature, while Section 3 formally describes the proposed approach and discusses its applicability. A case study in which this framework was applied for the development of an adaptation module for a CBR system supporting the design of a production process will then be introduced. Conclusions and future developments will end the paper.

2 Context and Related Work

Case adaptation is a very complex task: in fact, CBR is often selected as a problem solving method for situations in which a theory or model allowing to construct the solution of a given problem cannot be defined due to lack of knowledge. In these situations it is also very difficult to have a theory of adaptation, a set of mechanisms defining how to modify the solution of a case similar to the current one according to differences in their descriptions. The *null adaptation* approach (i.e. leaving the adaptation up to the user, or do not perform adaptation at all) is often selected, while relevant experiences in the modelling and design of adaptation models describe complex knowledge models requiring considerable knowledge engineering effort to be effectively implemented (see, e.g., [3, 4]).

Several works can be found in the literature that aim at describing possible approaches for the modelling and design of adaptation modules, and some of them are aimed at the development of general approaches and methodologies for case adaptation. In [5] it is described an attempt to combine retrieve and adaptation steps into a unique planning process, leading to the problem solution starting from the current problem description. In this way the general issue of adaptation is reformulated in terms of plan adaptation. Several other approaches provide the learning of adaptation rules from the case base itself [6]. In particular, while some of these approaches reify episodes of adaptation into cases and adopt a second CBR system devoted to this single step of the overall cycle (see, e.g. [7]), other ones adopt a hybrid strategy, including both such a CBR-based adaptation and rule-based modifications of the retrieved solution (see, e.g., [8]). Another relevant example of adaptation strategy provides the exploitation of domain specific relationships among cases (i.e. case dominance) to provide an adaptation heuristics supporting case-based estimation [9]. In particular, this approach exploits pairs of past solved cases presenting some specific difference with respect to the current one, in order to derive an adaptation to the retrieved case solution.

3 Framework for Substitutional Adaptation

The basic assumption of the CBR approach is that "similar cases of a certain problem have similar solutions": given the description of a new instance of a problem, one may search the set of previous experiences for a solved case characterized by a similar description and adapt its solution to the current situation. The first part of this process (i.e. to search for a similar case) relies essentially on the concept of similarity and knowledge related to the capability to compare cases. The second part is instead related to the capability to derive a modification to be applied to the solution of the retrieved case, from the descriptions of the current and retrieved ones in order to adapt the solution of the latter to be suitable for the current target case.

The rationale on which the proposed approach is based is that "similar differences among case descriptions imply similar differences among their solutions". In other words the same base of previously solved problem instances can also be queried for pairs of cases representing respectively the current and the retrieved case. These pairs are characterized by the fact that their descriptions present similar differences to the one that holds between the current and the retrieved cases. The differences among their solutions can thus be considered as indicators of the modification to be applied to the solution of the retrieved case to obtain the new one. A diagram describing this adaptation scheme is shown in Figure 1. The current and retrieved cases are respectively denoted by c_c and r_c, while r_{c_c} and r_{r_c} indicate their representatives; mod_c represents the modification to be applied to the solution of r_c in order to adapt it to the current case, and it is obtained as an aggregation of the differences among solutions of the representatives (i.e., $mod_1, \ldots, mod_n$).

In the following we will describe this approach in details and we will discuss its applicability.

3.1 Formal Description

In a CBR method, a case is a three–tuple $\langle d, s, o \rangle$, where d is the set of features that describe the specific instance of the problem, s is the set of attributes that characterize its solution, and o is the set of attributes describing the outcome obtained by the application of the solution s to the problem d. Given a Case Base CB, with $d(c)$, $s(c)$ and $o(c)$ we respectively denote the description, solution and outcome of a case $c \in CB$.

A case representation may provide a flat, fixed set of case descriptors or a more structured and possibly heterogeneous organization (see, e.g., [10, 11]); however a case description can always be reduced to a finite set of features (e.g. a tree structured case can be reduced to a vector including only the leaves).

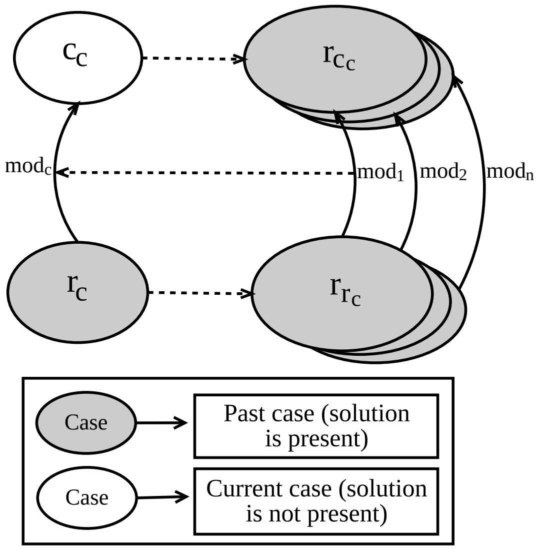

Fig. 1. Pairs of past cases representing the current and the retrieved one can be used to adapt the retrieved solution.

In the following we are thus going to consider a case as a finite set of features $\{c_1, \ldots, c_k\}$; moreover it will be assumed that cases have an homogeneous description d. Under these conditions a case having k attributes can be considered as a vector of a k-dimensional space; in this way it is possible to obtain from pairs of cases a vector indicating the (vectorial) difference among their description parts. Given $a, b \in CB$ having an homogeneous description d (with $l < k$ the number of attributes composing d), the distance vector among them can be defined as

$$dist(a, b) = \Big(\big(dist_1(a_1, b_1)\big), \ldots, \big(dist_l(a_l, b_l)\big)\Big) \tag{1}$$

where $dist_i$ represents the function that measures the distance among attributes at the i-th position in the case description d (e.g. normal difference for numeric attributes, specifically defined function for symbolic attributes). It must be noted that in general $dist(a, b) \neq dist(b, a)$.

Let us consider two cases $c_c \in CB$ and $r_c \in CB$, having an homogeneous description (i.e. a description providing the same number and type of features), and representing respectively the current case and the best–matching case in the Case Base according to the similarity function computation. It is possible to obtain pairs of case representatives $\langle r_{c_c}, r_{r_c} \rangle$ so that

$$r_{c_c}, r_{r_c} \in CB, \|dist(c_c, r_c) - dist(r_{c_c}, r_{r_c})\| < \epsilon \tag{2}$$

In other words these representatives (that are case belonging to the case base CB) are not selected because they are similar to the current and retrieved case, but because the difference among their description is similar to the one

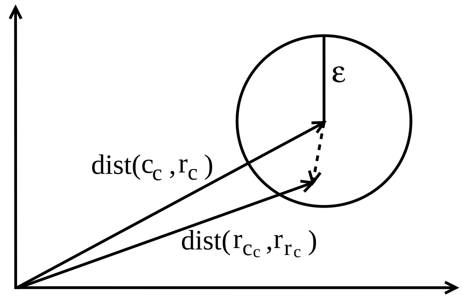

Fig. 2. A diagram illustrating the representative selection mechanism.

that holds between the descriptions of c_c and r_c. The vector norm of difference among vector $a = dist(c_c, r_c)$ and $b = dist(r_{c_c}, r_{r_c})$ can be computed in this way

$$\sum_{i=1}^{l} \left(w_i \cdot diff_i(a_i, b_i) \right) \tag{3}$$

where $diff_i$ represents the function adopted to evaluate differences among the i-th distances in case descriptions, whose relevance is modulated by means of weighs w_i; they are strictly related to $dist_i$ functions, but these are bound to have $\mathbb{R}^+$ as codomain. However this is just one possible way to evaluate the similarity of two differences among cases, and according to specific domain knowledge this kind of evaluation might assume a different form. An intuitive graphical representation of this method to select representatives is shown in Figure 2.

It must be noted that representatives are identified according to $dist_c = dist(c_c, r_c)$, which is a vector distance. More precisely, two cases a and b are chosen respectively as representatives of the current case c_c and the retrieved case r_c because of the similarity among their vector distance $dist(a, b)$ and $dist_c$ according to a given norm, such as the one defined in equation 3, and a threshold value ϵ. However, in general, nothing can be said on the possibility of inverting a and b and still having a pair of representatives. This is due to the fact that $dist(a, b) \neq dist(b, a)$, and thus the there is no indication on $\|dist(c_c, r_c) - dist(b, a)\|$.

Given this method for defining pairs of cases which, according to the differences among their descriptions, can be considered representatives of the current and retrieved cases, it is possible to denote the set of these representatives by $Rep_{(c_c, r_c, \epsilon)}$. According to the previously introduced principle "similar differences among case descriptions imply similar differences among their solutions" every pair of representatives of this set may give an indication on the modification to be applied to the retrieved case solution. To derive in an automatic way a modification to be applied to the retrieved case in order to obtain the solution to the current one, is not trivial and some specific conditions must be specified. First of all, we focus on those representatives whose solutions are homogeneous to $s(r_c)$ (i.e. whose solution has the same structure of the one specified by the

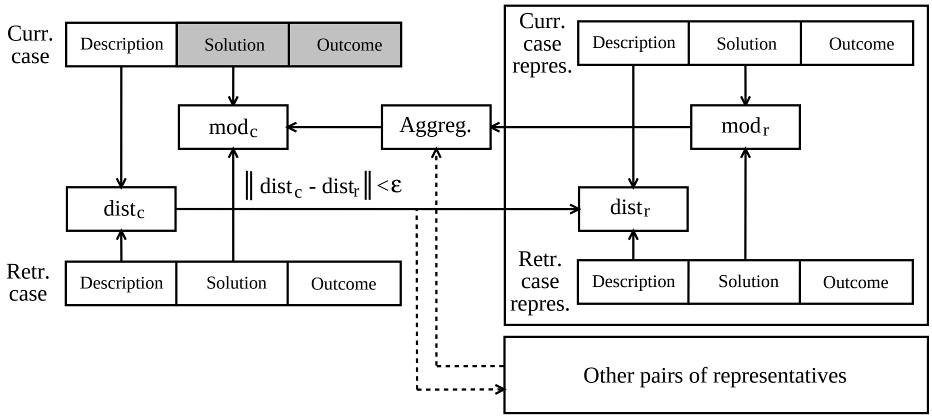

Fig. 3. A diagram illustrating in details the proposed adaptation framework.

retrieved case), which will be denoted by $HRep_{(c_c,r_c,\epsilon)}$. Thanks to this homogeneity, given a case c in $HRep_{(c_c,r_c,\epsilon)}$, its solution part is a vector of attributes $s(c) = \{s_1, \ldots, s_j\}$. Given s and s' vectors representing solutions to two different cases, the difference vector among s and s' can be defined as

$$mod(s, s') = \big(dist_1(s_1, s'_1), \ldots, dist_j(s_j, s'_j)\big) \tag{4}$$

where these $dist_i$ functions are analogous to those introduced for the computation of distance among cases in equation 1, with analogous considerations with reference to numeric and symbolic attributes. In other words, while distances and related modifications to numerical attributes can be easily computed, symbolic attributes require the definition of specific functions to compute this distance. Moreover, in this case we want to exploit this value to obtain indications on how to modify such an attribute in an adaptation scheme. The management and adaptation of symbolic attributes in case solution will be the object of future works, and we will now focus on numeric ones.

Considering that $s_1, \ldots, s_j$ are numerical attributes, it is possible to define the vector $mod(c_c, r_c)$ representing the modification to be applied to the retrieved case solution as a vectorial aggregation of the differences between solutions of case representatives. More precisely, given $H = HRep_{(c_c,r_c,\epsilon)}$,

$$mod(c_c, r_c) = \Big(\sum_{\langle c,r\rangle \in H} \big(f_{cr} \cdot dist_1(c, r)\big), \ldots, \sum_{\langle c,r\rangle \in H} \big(f_{cr} \cdot dist_j(c, r)\big)\Big) \tag{5}$$

where c and r respectively represent the current and retrieved case (in fact $\langle c, r\rangle \in HRep_{(c_c,r_c,\epsilon)}$). The multiplicative factor f_{cr} represents instead the relevance of the pair of representatives $\langle c, r\rangle$ in determining the overall adaptation vector mod_c. This factor can be a constant (e.g. $\frac{1}{|HRep_{(c_c,r_c,\epsilon)}|}$), or a function encapsulating domain knowledge which allows to distinguish pairs of representatives. The vector mod_c represents the modification to be applied to the solution of the retrieved case in order to obtain the new solution for the current case.

A schematic illustration of the whole process of representatives selection and aggregation of modifications to compose the adaptation vector is shown in Figure 3. In particular, *dist* and *mod* blocks are respectively related to equation 3 and 4, while the *Aggreg.* block is related to equation 5.

3.2 Applicability of the Proposed Approach

In the previous Section the proposed framework for substitutional adaptation has been formally described; some constraints on the structure of cases on which this framework can be applied were briefly introduced, but this section will discuss the applicability of this approach, with specific reference to two main aspects, that are case structure and the type of attributes that compose its solution part.

With reference to case structure, hierarchical and even graph–based approaches are being growingly considered and adopted for case representation, due to their expressive power and suitability to represent complex case descriptions, but flat structures are still commonly adopted for CBR systems development. This kind of representation provides the description of a case in terms of a fixed number of attribute–value pairs. This kind of structure does not present particular problems with respect to this approach. In this framework, cases having a non-flat structure (e.g. hierarchies) do not present different problems, provided that their structure is fixed and not variant from case to case. In fact this kind of structures can be reduced to a flat set of attribute-value pairs composing the case base (e.g. leaves of a tree–structured case).

The actual crucial factor for the approach applicability is the variability of the case structure. If the case base is made up of non-homogeneous cases, presenting different descriptions or solutions, the previously introduced mechanisms for the computation of distances introduced in equation 1 must be modified. While there are existing approaches focused on the computation of similarity among the heterogenous descriptions of cases (see, e.g., [10, 12, 11]), which could be adopted in this case to measure distances, the problem of computing differences among solutions (equation 4) and especially to exploit them in order to obtain an adaptation of the retrieved case solution (equation 5) is the object of current and future works. Moreover this goes beyond the simple substitutional adaptation approach, and possibly provides a structural modification of the proposed solution.

The simplest strategy for the application of this approach in a flexible case situation is to limit the search for representatives to those cases whose structure provides description and solution parts that are homogeneous to the one provided by the current and retrieved case. In this way, the flexibility of case representation is not exploited (cases with a different structure are simply ignored by the adaptation mechanism), and the situation is reduced to a homogeneous scenario.

Another relevant aspect is determining the applicability of the approach is the type of attributes that compose the solution part of the case. The introduced approach can manage numeric attributes in a very simple way, while symbolic attributes require some additional work in order to be managed automatically. The main issue is the aggregation of differences among values related to a symbolic attribute in solutions of case representatives in order to derive that component of the adaptation vector. To manage this operation in an automatic way a sort of algebra for that kind of symbolic attribute should be defined. Another possible approach is to perform adaptation only for numeric attributes and report the user on the set of possible modifications on symbolic attributes related to the identified representatives, leaving him/her the choice on that component of the adaptation vector.

It must be noted that the only domain knowledge exploited in this process, and thus required by the approach, is essentially related to the capability to measure differences among cases and their attributes (i.e. *dist* and *diff* functions in equations 1, 3 and 4) and to attribute relevance (i.e. weights in equation 3 and multiplicative factors in equation 5) to these differences, in other words *analogical* knowledge. Essentially this kind of approach does not require the typical additional knowledge (e.g. procedural domain knowledge) required to implement an adaptation module. However it also allows to include some specific domain knowledge, for instance to select which pairs of representatives have more influence on the overall modification to be applied to the retrieved case solution. A more through analysis of possible ways to integrate this approach with non-analogical domain knowledge (e.g. partial heuristics or procedural knowledge), is also object of current and future developments.

4 A Case Study: P-Truck Curing

The case study which will be presented in this Section is related to the design and development of P–Truck Curing, a Case Based Reasoning system supporting the design of the curing phase for truck tyre production. A truck tyre is composed of both rubber compounds and metallic reinforcements: the former are responsible for all the thermal and mechanical properties of the tyre; on the other hand, metallic reinforcements give it the necessary rigidity. Once all the semi–manufactured parts are assembled into a semi–finished product (in jargon called *green–tyre*), the latter undergoes a thermal treatment (vulcanization) that activates reactions between polymers, in order to give it the desired properties, such as elasticity, strength, and stability. The curing process provides different phases of external or internal heating, and internal inflation of the green–tyre carcass. To design a curing process the expert evaluates the characteristics of the green–tyre and then, for every step of the process, he/she decides starting instant and duration, temperature and pressure of the involved fluids. Variants to standard procedures can also be suggested (for instance to slightly modify the typical value of factory dependent parameters). Problem analysis began with meetings and interviews with expert curing process designers, also referred to as curing technologists. Early stages of knowledge acquisition made clear that any of these experts uses to store information related to curing processes, de-

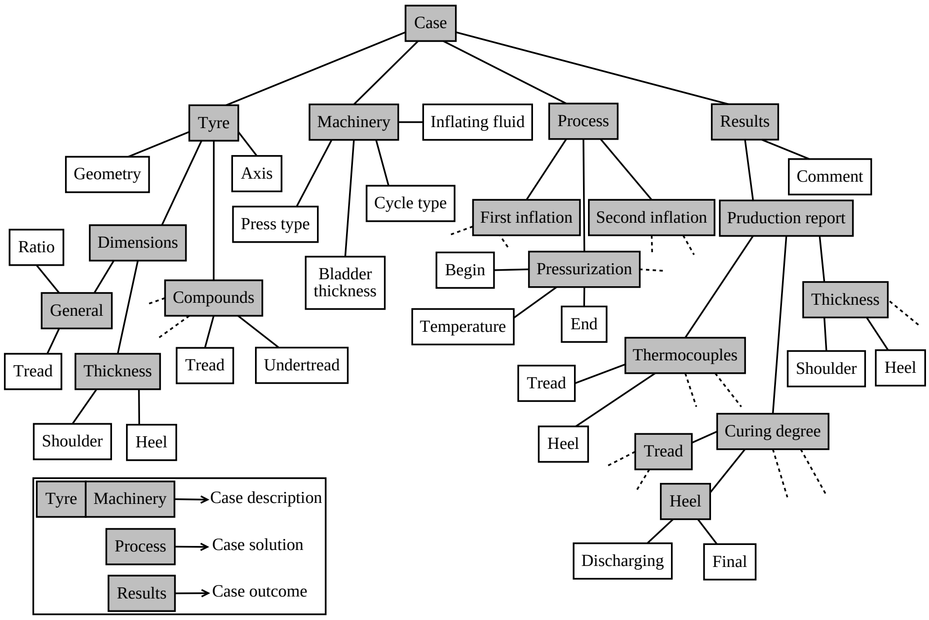

Fig. 4. Case structure: the diagram shows a partial view of the tree–structure related to a case.

signed both by himself/herself and by other technologists. These notes concern incidental problems, adopted solutions, variants of process and results, both positive and negative, about tyre curing. When a technologist has to design a new curing process he/she uses these information and his/her experience to define its details, without starting from scratch or using formally well–defined rules. A CBR system is thus a suitable approach to model this problem solving method. Figure 4 shows a partial view of the case structure, which is hierarchical and fixed. In particular the high-level components of this structure are related to tyre (e.g. dimensions, composition) and curing machinery (e.g. temperature and fluids), which compose the case description, curing process specification, that represents case solution, and process evaluation, which is related to case outcome. A detailed description of P–Truck Curing is out of the scope of this paper and can be found in [13]; this Section will instead focus on a description of how the previously introduced framework for substitutional adaptation was applied to this specific situation.

A CBR approach was adopted because of its suitability to represent expert's decision making process but also because knowledge on the domain (in particular procedural knowledge) is very limited. As previously specified, a green–tyre is a composite object, and even if some basic principles are known (e.g. thicker parts of a tyre require more energy to reach an optimal curing degree), to compose them in order to obtain a globally optimal process result is a very complex task. For instance, different tyre parts could require a completely different process

	Thickness	Axis	Fluid	Chamber	Duration	Result
c_c	40	T	H_2O	8		
r_c	41	T	N	8	48.3	7
a	42	T	N	6	53.8	6
b	43	T	N	6	54.9	6
c	45	T	H_2O	8	57	5
d	43	T	N	8	55	7
e	43	T	H_2O	8	55.1	6

Table 1. A sample adaptation scenario for P-Truck Curing.

modification (i.e. sidewalls are thinner and thus require less energy, while shoulders are thicker and require more), and some components do not have a clear influence on the global result (e.g. metallic parts). Nonetheless the adopted approach aims to supply to the designer an indication of how to adapt the retrieved solution to the current case according to past experiences.

4.1 Curing process adaptation

The adaptation to the retrieved case solution is based on pairs of past cases presenting differences similar to the one that holds between the current case and the retrieved one. In particular, for every field which is different in the description of the retrieved case a pair of representatives having the same difference among their description is chosen, in order to define a part of the overall adaptation which is due to that specific difference. The choice is based on a numerical evaluation of the cases composing the pair (i.e. successful cases are more likely chosen as representatives). The idea is to consider differences that cause the adaptation step, and discover what such differences meant in the past in terms of differences in case solutions. These differences are indicators of how the retrieved case should be modified to better fit the new situation. These consideration must be considered as specific domain knowledge that has an influence on representatives selection and modification aggregation.

Consider the adaptation scenario described in Table 1; a simplified version of curing case is presented, for sake of simplifying the example and also for confidentiality reasons. The described attributes are related to

- elements of case description: tyre thickness and axis, curing press inflating fluids and bladder thickness;
- case solution: curing process duration;
- outcome: numeric evaluation of process results.

Elements c_c and r_c represent respectively the current and retrieved case, while $a, b, c, d, e \in CB$ are cases belonging to the case base. The pairs $\langle a, b\rangle$ and $\langle e, d\rangle$ are selected as representatives of c_c and r_c, in fact the first pair presents the same difference in tyre thickness, while the second presents the same difference in the inflating fluids exploited by the curing machinery. While the solutions related to the first pair indicate that the duration of the retrieved case should be reduced ($s(a) - s(b) = -1.1$), the other pair suggests to increase it ($s(e) - s(d) = 0.1$). According to multiplicative factors specified for equation 5, and thus to specific domain knowledge, a combination of the two modifications will determine the overall adaptation to be applied to $s(r_c)$. In particular, in this case, tyre thickness is considered a more important factor than the adopted inflating fluid, so the overall modification will decrease the process duration but less than the only pair $\langle a, b \rangle$ would suggest.

5 Conclusions and Future Delevelopments

In this paper a general framework for substitutional adaptation based on analogical knowledge was introduced and formally described. Its applicability was discussed with specific reference to the structure of cases and their variability, and also with reference to the types of attributes of case solution part. The main feature of this approach is that the only kind of knowledge required to implement it is related to the capability to measure differences and distances among cases and to define the relevance of these measures. Thanks to this kind of knowledge it is possible to select representatives of current and retrieved cases, and exploit the differences among their solutions to adapt the retrieved case solution.

The approach is actually the generalization of a concrete experience described as a case study, which provides the adaptation of cases related to truck tyre production processes. The module was designed and developed in close collaboration with expert curing process designers, which validated the approach. The module is currently being tested and effectively applied in order to fine-tune the related parameters. This adaptation scheme is also being considered for application in other projects providing the adoption of CBR as problem solving method.

Current and future works related to this framework are aimed at a more through analysis of possible ways to integrate additional domain knowledge (e.g. partial heuristics, incomplete procedural knowledge) in the adaptation scheme, and also on possible ways to support the generalization of adaptation experiences and their reification into more comprehensive forms of adaptation knowledge, towards the construction of domain specific adaptation theories and models.

The approach is focused on substitutional adaptation, and it is not well suited to manage and exploit variability in case structure. The exploitation of the basic principle of this approach in the context of structural or generative adaptation scenarios is also object of future investigations.

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