In: Case-Based Reasoning: Processes… ISBN: 978-1-61728-352-9
Editors: Antonia M. Leeland

Chapter 1

CASE-BASED REASONING INTEGRATIONS: APPROACHES AND APPLICATIONS

***Jim Prentzas*[a,*b] *and Ioannis Hatzilygeroudis*[a,**]**

[a] University of Patras, School of Engineering Department of Computer Engineering & Informatics, 26500 Patras, Greece.

[b] Democritus University of Thrace, School of Education Sciences Department of Education Sciences in Pre-School Age, 68100 Nea Chili, Alexandroupolis, Greece.

ABSTRACT

A popular approach in Artificial Intelligence involves integration or combination of (two or more) representation methods. The integrated components offer advantages to the overall system. Integrated approaches have been applied to various application domains demonstrating their effectiveness in knowledge representation and reasoning. Integrations of case-based reasoning with other intelligent methods have been explored deriving effective knowledge representation schemes. Case-based reasoning is usually combined with rule-based reasoning, model-based reasoning and soft computing methods (i.e., fuzzy methods, neural networks, genetic algorithms). Certain types of case-based reasoning integrations have been extensively explored. However, other types of

* Email: dprentza@psed.duth.gr.
** Corresponding author: Email: ihatz@ceid.upatras.gr.

combinations have not been adequately investigated, which leaves room for extensive research work. In this chapter, we illustrate basic types of case-based reasoning integrations. A categorization scheme for such integrations is provided and the functionality of specific approaches combining case-based reasoning with other intelligent methods is presented. The focus is on integrations dealing with innovative ideas and representing research areas that need to be explored. The chapter also outlines a formalism combining case-based reasoning with neurules, a type of hybrid rules integrating symbolic rules with neurocomputing. Moreover, future directions are pointed out.

Keywords: case-based reasoning integrations, hybrid case-based reasoning, case-based reasoning combinations, hybrid intelligent systems, integrated intelligent systems, hybrid knowledge representation and reasoning, case-based reasoning.

1. INTRODUCTION

The combination or integration of (two or more) different problem solving and knowledge representation methods has proven effective in many application areas [49]. The aim is to create combined formalisms that benefit from each of their components. Disadvantages or limitations of specific intelligent methods can be surpassed or alleviated by their combination with other methods. It is worthwhile to explore combinations of different intelligent methods in case their advantages and disadvantages prove to be complementary to an adequate degree. Popular integrations are neuro-symbolic approaches, combining symbolic representations with neural networks [7], [29], neuro-fuzzy approaches, combining fuzzy logic and neural networks [52], approaches combining neural networks with genetic algorithms [2], approaches combining fuzzy or neuro-fuzzy systems with genetic algorithms [2] and approaches combining case-based reasoning with other intelligent methods [46], [47], [6], [61], [63]. Other integrations have been developed as well.

Case-based reasoning (CBR) exploits stored past cases whenever a similar new case needs to be dealt with [1], [38], [39], [18]. Cased-based inference is performed in four phases known as the CBR cycle [1]: (i) *retrieve*, (ii) *reuse*, (iii) *revise* and (iv) *retain*. The retrieval phase retrieves from the case base the most relevant stored case(s) to the new case. In the reuse phase, a solution for the new case is created based on the retrieved most relevant case(s). The revise phase validates the correctness of the proposed solution, perhaps with the intervention of the user. Finally, the retain phase decides whether the knowledge learned from the solution of the new case is important enough to be incorporated into the system. CBR is a useful approach in domains with a sufficient number of available (or obtainable) cases and does not require existence of an explicit domain model.

Integrations of CBR with other intelligent methods have been pursued in various domains. In such combinations, the combined system offers advantages in knowledge representation and reasoning compared to each of the combined methods working alone. CBR has been integrated with intelligent methods such as rule-based reasoning (RBR), model-based reasoning (MBR), fuzzy methods, neural networks, probabilistic reasoning, genetic algorithms and other methods as well.

When two or more intelligent methods are combined, different integration models can be employed [49]. Not all types of combination models have been employed in CBR integrations. An aspect of interest involves pointing out trends in CBR integrations in which there is room for extensive research work. A trend that needs to be explored further concerns approaches in which the problem solving process can be decomposed into subprocesses (tasks or stages) for which different representation formalisms are required or available. In such situations, a CBR system as a whole (with its possible internal modules) is integrated ‘externally’ with other intelligent systems in order to create an improved overall system. An interesting aspect of this combination trend is that different types of such combinations can be developed. This trend has been explored thoroughly for integrations of CBR with RBR and MBR but not for integrations of CBR with other methods. Another trend that could also produce fruitful results involves approaches in which CBR is embedded within another intelligent method. Such approaches have been explored in integrations of CBR with genetic algorithms. However, they could prove to be effective in integrations of CBR with other intelligent methods as well. Moreover, combinations of CBR with certain specific intelligent methods have not been explored extensively. Such intelligent methods involve for instance the various neuro-symbolic approaches.

Due to the fact that several approaches integrating CBR with other intelligent methods have been developed, it is necessary to discuss issues involving main trends in such combinations that have been applied. In this discussion it is also necessary to point out interesting open aspects for future work. In this chapter, we discuss various aspects involving CBR integrations. We focus on key aspects involving CBR integrations and discuss the potential for future research work. We also briefly present an approach combining CBR with neurules, a neuro-symbolic knowledge representation scheme. Neurules are a type of hybrid rules integrating symbolic rules with neurocomputing [25], [26] and exhibit certain attractive features such as naturalness and modularity. Such an approach integrates three intelligent methods: symbolic rules, neural networks and CBR [28].

The purpose of the discussion included in this chapter is threefold. We believe that it will increase understanding of the field concerning integrations of CBR with other intelligent methods. In addition, it may lead to development of new (or overlooked) ways of combining CBR with other intelligent methods. Finally, it is a useful guide to developers/designers of such systems.

The structure of the chapter is as follows. Section 2 discusses issues involving main trends in CBR integrations. This discussion serves as background knowledge for the following sections. Section 3 briefly presents representative approaches of specific types of CBR integrations that could provide impetus for future research work. In section 4, we present an outline of an approach combining CBR with neurules. Finally section 5 concludes.

2. TRENDS IN INTEGRATIONS OF CBR WITH OTHER INTELLIGENT METHODS

Various CBR integrations have been developed [63], [61], [46], [47]. To develop such integrations, existence of (or ability to acquire/construct) necessary knowledge sources corresponding to each of the combined methods is required. Other criteria may also be specified to judge whether an approach combining CBR with other intelligent method(s) could be applied to a specific domain [63].

To categorize CBR combinations one could use Medsker's general categorization scheme for integrated intelligent systems [49]. Medsker distinguishes five main combination models: *standalone*, *transformational*, *loose coupling*, *tight coupling* and *fully integrated models*. Distinction between those models is based on the degree of coupling between the integrated components.

In [61] Medsker's categorization scheme was extended and revised to accommodate recent advances in integrations of CBR with RBR. This new scheme provides a more consistent view to modeling integrations of CBR with other intelligent methods. Figure 1 depicts the categorization scheme for CBR integrations, based on that in [61]. For each (sub)category, intelligent method(s) with which CBR has been combined is shown besides each (sub)category. An unexplored type of CBR integration is indicated by a broken rectangle. In Figure 1, ‘GA’ stands for ‘genetic algorithm’ and ‘NS’ for ‘neuro-symbolic approaches’. It should be mentioned that in [61] deficiencies of other categorization schemes for CBR integrations (e.g. [46], [47], [23]) are discussed.

Two main categories of CBR integrations are discerned in our categorization scheme: (a) standalone and (b) coupling approaches. Three main types of coupling approaches can be distinguished: (i) sequential processing, (ii) co-processing and (iii) embedded processing.

In standalone models, independent components of each approach are developed that do not interact with each other during reasoning. They can be used in parallel to compare the independent solutions providing an opportunity to compare the capabilities of each approach.

In sequential processing, the flow of information (produced by reasoning) between the integrated modules is sequential or semi-sequential. It includes approaches in which information necessarily passes sequentially through some or all of the combined components in order to produce the final result. Two subcategories of the sequential category are distinguished: the ‘loosely coupled sequence’ and the ‘tightly coupled sequence’ subcategories. The former involves approaches in which the output of one component does not play an important role in the internal reasoning process of the next component. The latter concerns approaches in which the output of one component plays a significant role in the internal reasoning process of the next component.

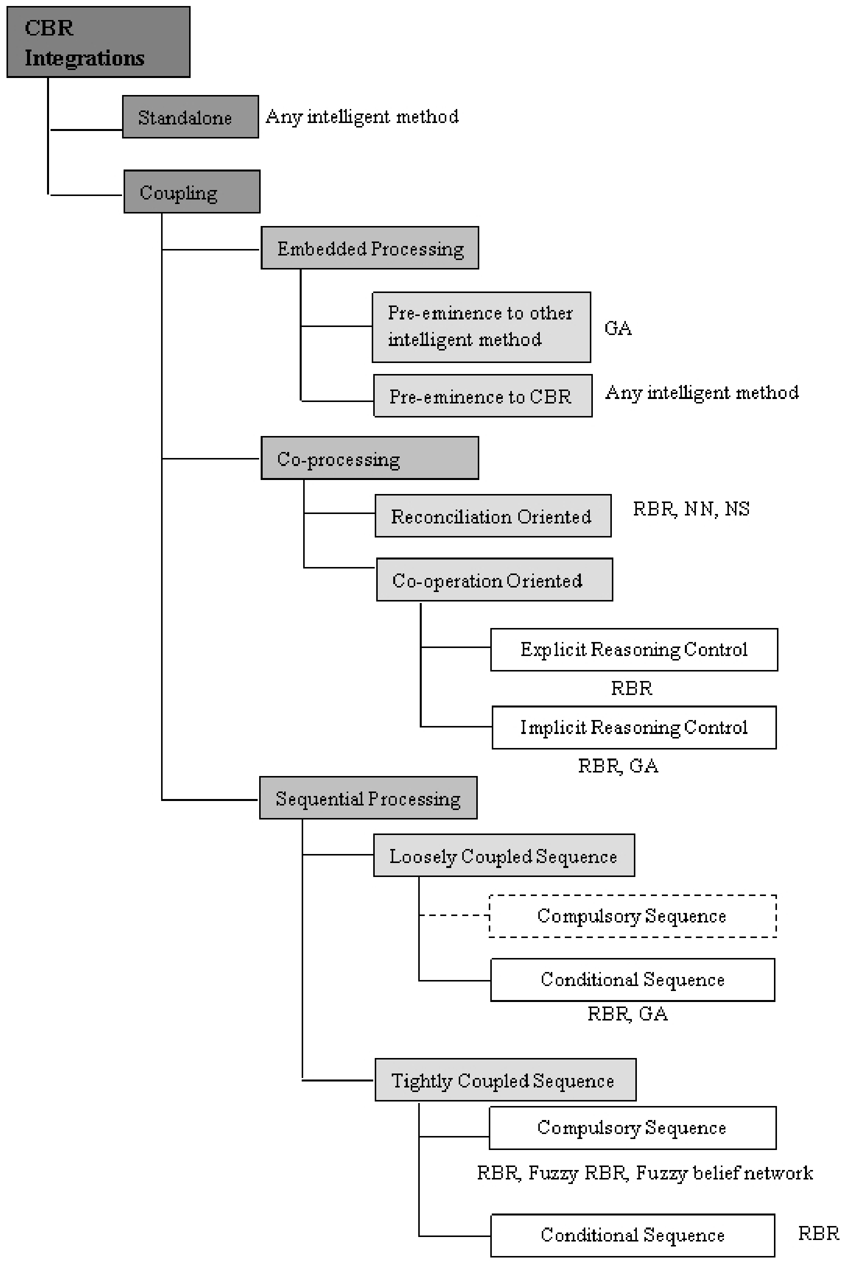

Figure 1. Categorization scheme for CBR integrations.

The tightly coupled subcategory is distinguished into two subcategories: compulsory sequence and conditional sequence. In compulsory sequence, a component is invoked unconditionally after the previous component in the sequence. In conditional sequence, the second component is invoked if the first one fails to provide a solution. All approaches belonging to loosely coupled sequence follow the conditional sequence pattern. An aspect of interest in sequential processing concerns the invocation order of the integrated components and more specifically, whether CBR is invoked before or after the other integrated components. In all existing sequence approaches but the tightly coupled conditional sequence approaches, CBR is invoked before or after invocation of other combined component(s). In existing tightly coupled conditional sequence approaches, CBR is invoked after the other integrated component(s).

In co-processing, the integrated components closely interact during reasoning. To produce output, flow of data between the components is bidirectional enabling an enhanced form of interaction. The integrated components may be also invoked in parallel to solve the problem. Approaches belonging to the co-processing category are distinguished to cooperation oriented and reconciliation oriented according to whether emphasis is given to cooperation or reconciliation respectively. In cooperation oriented approaches, the integrated components cooperate with each other during inference. In reconciliation oriented approaches, a reconciliation process is necessary since each integrated component produces its own conclusion, possibly differing from the conclusion of the other component. Cooperation oriented approaches may either employ explicit reasoning control or implicit reasoning control. The former approaches employ an explicit controller or explicit control knowledge to coordinate reasoning. The latter approaches coordinate reasoning implicitly.

In embedded processing, a component based on one approach is the primary problem solver, embedding component(s) based on other representation method(s) to handle its internal reasoning tasks. Embedded processing approaches can be distinguished into those giving pre-eminence to CBR and to those giving pre-eminence to other method. In the former, a CBR system embeds other intelligent method(s) to assist various internal CBR tasks. Internal CBR tasks can be implemented using various techniques [73], [14], [53]. The latter involve the reverse (and less usual) approach i.e. embedding CBR within other representations to assist in their internal tasks.

Not all of these combination models and/or their underlying categories have been thoroughly explored in combinations of CBR with other intelligent methods. Obviously, the standalone model can be applied in combinations of CBR with any other intelligent method. In combinations of CBR with certain methods (e.g. RBR, MBR), various coupling approaches have been investigated [61], [46], [47]. However, in coupling combinations of CBR with soft computing methods, embedded approaches seem to be the most thoroughly investigated. Embedded coupling approaches mainly concern those giving pre-eminence to CBR. Embedded coupling approaches giving pre-eminence to other intelligent method do not seem to be popular with the exception of genetic algorithms (see Section 3.3).

Combinations of CBR with other intelligent methods can offer advantages to the overall system especially in case the advantages and disadvantages of the combined methods are to a certain degree complementary. CBR provides advantages to the overall system such as easy knowledge acquisition by exploiting available (or obtainable) cases, naturalness, modularity, incremental learning and certain explanation facilities. Other intelligent methods when combined with CBR may offer advantages to the overall system such as the following:

Table 1. Application domains and intelligent methods CBR has been integrated with.

Application Domain	Intelligent Method(s) CBR has been integrated with
Agriculture	RBR
Aircraft Design	RBR
Aircraft Fleet Maintenance	RBR
Automobile Construction	RBR
Banking	RBR
Biomedicine	RBR
Construction	RBR
Design of Nutrition Menus	RBR
E-learning, Intelligent Tutoring	RBR, GA
Emergency Fire Management	GA
Environmental Impact Assessment	Fuzzy RBR
Equipment Failure Analysis	RBR
Finance	RBR, Possibilistic RBR
Legal Reasoning	RBR
Life Insurance	RBR
Medicine	RBR, Fuzzy RBR
Modeling Event-based Dynamic Situations	RBR
Music	RBR
Personnel Performance Evaluation	RBR

Quality of Service	RBR
Real-Time Marine Environment Monitoring	RBR
Situation and Threat Assessment of Ground Battlespaces	Fuzzy belief network
Surname Pronunciation	RBR
Ultrasonic Rail Inspection	RBR

- RBR provides general and compact available domain knowledge in the form of rules and rule-based explanation facilities.
- Fuzzy methods provide imprecision handling and (in case of fuzzy RBR) fuzzy rule-based domain knowledge.
- Neural networks provide robustness, generalization, learning capabilities, classification/clustering capabilities.
- Genetic algorithms provide search and optimization facilities, compact representation of problem parameters and representation of possible solutions.
- Neuro-symbolic approaches provide (more or less) the combined advantages of symbolic methods and neural networks.
- Neuro-fuzzy approaches provide (more or less) the combined advantages of fuzzy methods and neural networks.

Table 2. Application domains and systems integrating CBR with other method.

Application Domain	Integrated Approaches
Agriculture	[78]
Aircraft Fleet Maintenance	[75]
Banking	[41]
Biomedicine	[55]
Construction	[20]
Design of Nutrition Menus	[45]
E-learning, Intelligent Tutoring	[31]
Emergency Fire Management	[8]
Environmental Impact Assessment	[43]
Equipment Failure Analysis	[33]
Finance	[16], [19]
Legal Reasoning	[64], [10], [11], [77], [12]
Life Insurance	[40]
Medicine	[9], [48], [51], [58], [65], [21]
Modeling Event-based Dynamic Situations	[34]
Music	[66]
Personnel Performance Evaluation	[17]
Quality of Service	[24]

Real-Time Marine Environment Monitoring	[71]
Situation and Threat Assessment of Ground Battlespaces	[44]
Surname Pronunciation	[23]
Ultrasonic Rail Inspection	[35]

Tables 1 and 2 summarize the application domains in which non-embedded CBR combinations have been developed. For each domain, Table 1 depicts the intelligent method(s) CBR has been integrated with. Table 2 depicts specific systems for each domain. It should be mentioned that some of the systems depicted in Table 2 whose application domain does not strictly concern e-learning have been employed as teaching assistants. Such systems are presented in [9], [21]. Moreover [78] is also reported that could be used as a teaching assistant. It should be mentioned that several integrated approaches do not involve specific application domains and their effectiveness has been tested with datasets.

Generally speaking, the following unexplored research directions regarding CBR integrations can be discerned:

- Implementation of CBR combinations with specific intelligent methods according to all (or most of) integration categories shown in Figure 1. For instance, combination of fuzzy RBR with CBR can follow the different coupling models concerning integration of RBR with CBR.
- In several application domains shown in Table 1, integrations of CBR with specific intelligent methods have not been applied.
- Implementation of (non-embedded) CBR combinations in other application domains besides the ones shown in Tables 1 and 2.
- Implementation of tightly coupled conditional sequence approaches in which the CBR component is invoked before the other component(s).

3. Representative Systems

In the following, some representative systems involving integration of CBR with other intelligent method(s) are presented in some detail, to give a better insight of the corresponding categories of the categorization scheme described in the previous section.

3.1 Sequential Processing Approaches

We present systems belonging to the sequential processing coupling category in two sections. One involves loosely coupled sequence approaches and the other one tightly coupled sequence approaches.

3.1.1 Loosely coupled sequence

The loosely coupled sequence approaches presented in this section come from [70], [16], [24], [8] and [48]. In all these approaches, except [48], the CBR component is invoked after the other component.

In [70] a general integrated approach for the classification task is presented. In this approach rules represent standard situations and cases represent exceptions or non-standard situations. The contents of the knowledge base are produced from an initial case base whose cases are split into two types: standard cases and exception cases. Standard cases are used to induce the rules of the knowledge base. The CBR module works with the exception cases. Splitting the initial case base is performed using heuristic approaches. For an input case, the inference process first checks if the rules can produce a conclusion. If they do, inference ends, otherwise CBR is employed. An advantage of the approach, as demonstrated by various experiments, is the good explanation ability stemming from the high level of comprehensibility of the rules. This is due to the fact that the rules induced from the standard cases are closer to expert rules than the rules produced from the whole dataset of cases (standard and exceptional). However, as is shown in [70], the splitting policy of the initial case base plays an important role in the accuracy and comprehensibility levels of the approach.

ECLAS [16] is a loan authorization system. The knowledge regarding the domain is discerned into two types: (a) objective, which is logical, explicit and rational and (b) subjective, which is implicit, uncertain and imprecise. RBR corresponds to the objective knowledge, whereas the subjective knowledge corresponds to CBR. During reasoning, the rule-based module is first invoked to process the input case (i.e., a loan application). If the rule-based module rejects the application, inference stops. Otherwise, if it approves it, the CBR module is invoked for further examination of the application so that the final decision on acceptance or rejection will be made. In ECLAS, the rule-based module filters several input cases that are rejected thus reducing the case match load of the case-based module.

In [24] a service-oriented event correlation approach is presented. Service fault management is important issue for service providers as it affects the quality of services delivered to customers, revenue (i.e. customer satisfaction) and costs concerning fault management itself and service level agreement violations. The approach performs automated event correlation by modeling services, resources and faults. Rules involve event, condition and action statements. The RBR component is first invoked and if it fails the CBR component is invoked. Advantages of the specific approach involve maintainability, modeling, robustness (i.e. ability to reach conclusions even when the knowledge base is inaccurate and ability to update knowledge base after a failed diagnosis) and time-performance.

In [8] an agent-based approach to manage emergency fires inside large oil storage and production plants is presented. Management involves fire-proof resource optimization and dangerous product evacuation. The approach concerns three different types of agents: a simulation agent to simulate physical/chemical phenomena and their consequences, a genetic agent to produce optimal management solutions and a CBR agent to adapt stored cases to the current scenario. Emergency process time is short (i.e. some minutes). The genetic agent is first invoked and if it is not able to produce a solution within specific time limits, the CBR agent is then invoked.

In [48] a medical system for the care of Alzheimer’s disease patients is presented. The system provides decision support for neuroleptic drug prescription to patients with behavioral problems. The case-based module is invoked to determine if a neuroleptic drug should be prescribed to a patient and, if this is so, the rule-based module is invoked to select one of five such drugs. Such a system may improve the quality of life for Alzheimer’s disease patients.

3.1.2 Tightly coupled sequence

The tightly coupled sequence approaches presented in this section come from [45], [71], [78], [20], [75], [43], [44], [15], [13], [35], [55], [65] and [41]. Table 3 depicts the tightly coupled sequence approaches involving compulsory sequence and the ones involving conditional sequence.

Table 3. Representative tightly coupled sequence approaches.

Compulsory Sequence	[45], [71], [78], [20] [75], [43], [44], [15]
Conditional Sequence	[13], [35], [55], [65], [41]

CAMPER [45] is a nutritional menu planner built by combining the best features of two independent menu planners, a case-based and a rule-based, namely CAMP and PRISM. Nutritional menu planning is a difficult task, because there are many numeric constraints some of which conflict with others, menus can be evaluated only if they are entirely constructed and common sense must be employed for combinations of foods that match or do not match. CAMP and PRISM were evaluated and compared, in order to locate their deficiencies and strengths. This analysis (resembling the standalone model) guided the construction of CAMPER. The CBR component constructs menus that are acceptable, since they satisfy multiple nutrition constraints. However, the rule-based component can enhance the proposed menu with new possibilities, by employing common sense and performing ‘what if’ analysis. Menus enhanced by rules are inserted into the case base, thus improving the effectiveness of the case-based module. CBR in CAMPER always produces an output that is subsequently improved by the invocation of rules (unless the menu produced by CAMP is deemed quite satisfactory). As in GYMEL [66], a significant reason for the usefulness of the combination is the difficulty in the acquisition of cases.

CORMS AI [71] is a real-time monitoring system assisting National Ocean Service watch standing personnel in its monitoring duties seven days per week. The system also includes a database to collect real-time sensor data. Based on the real-time data, the system invokes the rule-based module to identify problems and then the case-based module to recognize the source of each problem and to suggest appropriate remedial actions. CORMS AI has proven to be effective and robust during its operation decreasing the amount of time required by the personnel to identify and handle problems. It is estimated that the financial gain for the US government due to the operation of CORMS AI will be over one million dollars per year.

HIDES [78] is a system for diagnosing crop injury from herbicides. Although several intelligent systems have been developed in the weed science domain, no such system assisted in herbicide injury diagnosis. Herbicide diagnosis is a domain that is understood reasonably well but not perfectly and therefore integration of RBR and CBR offers benefits. Diagnosis is based on nine critical inputs. RBR is first invoked to identify suspect herbicide families, suspect herbicide(s) for causing the observed injury and to determine possible sources of the suspect herbicide(s). RBR also identifies the. These results are passed to CBR to propose a probable cause of injury (e.g. improper soil condition or herbicide carryover). The system can be used as an educational tool for both traditional classroom and extension classroom.

ScheduleCoach [20] is a system used to critique construction schedules. Due to the increasing complexity and scale of construction projects, construction schedules frequently contain errors that can be difficult to find. ScheduleCoach uses critique rules representing experts' critiquing principles to identify potential errors in a construction schedule. Cases represent previous successful projects. Some rules contain predetermined suggestions for the revision of objects violating schedule principles. Fired rules not containing such predetermined suggestions cause the invocation of the CBR module to determine appropriate revisions for the violating objects.

IDS [75] is a system used to improve aircraft fleet maintenance. It locates possible faults providing their complete description, the corresponding symptoms and the remedial actions. The system includes multiple rule bases performing different diagnostic actions. Rules take as inputs (real-time or offline) messages generated by diagnostic routines and locate faults providing their complete description as well as the corresponding symptoms. The case-based module is then invoked to find cases with similar symptoms and suggest appropriate remedial actions.

In [43], an approach combining CBR with fuzzy RBR is presented for risk prediction in environmental impact assessment. Environmental impact assessment concerns analyzing effects regarding development proposals before major decisions are taken and commitments are made. CBR is used to store past cases involving environmental impact statements and environmental impact assessment reports. Fuzzy RBR models expert knowledge concerning qualitative risk prediction. The linguistic terms used in fuzzy RBR provide naturalness and expressiveness in risk assessment. CBR is first invoked to retrieve similar past cases. Afterwards, fuzzy RBR is invoked taking as input the retrieved cases and performs qualitative risk prediction.

In [44] an approach combining CBR with a fuzzy belief network is described. The application domain concerns situation and threat assessments of ground battlespaces. Situation assessment infers relevant information about forces of concern in a military situation. It is a prerequisite to threat assessment which analyzes enemy intentions and capabilities. Situation assessment is performed by CBR and threat assessment by the fuzzy belief network. Four systems are invoked sequentially with the results of each system passed on to the next one in the sequence: three CBR systems and lastly a fuzzy belief network. All CBR systems take as input clustered features of detected ground target(s) in a specific area of the battlespace. The respective output produced by each CBR involve unit type, unit size and unit purpose. These three outputs are given as input to the fuzzy belief network.

HACM [15] concerns a conditional sequence approach to solve potential lawsuit problems caused by change orders in construction projects. The purpose is to avoid and resolve disputes before litigation occurs. HACM combines a back propagation neural network with CBR. The neural network is first invoked to determine whether there is likelihood for litigation concerning the given input case or not. If the neural network determines that there is no likelihood for litigation, reasoning ends. Otherwise the CBR module is invoked to retrieve similar past cases and displays warnings if degree of similarity exceeds 95%. The weights of the neural network are used to calculate similarity.

ELEM2-CBR [13] is a system integrating rules and cases to perform classification and numeric prediction. Rules are produced from cases using a rule induction method called ELEM2. However, in the reasoning process both rules and cases are used. Similarities between cases are determined in an innovative way by using relevance weighting. The induced rules are used to determine the weights of attribute-value pairs of the input case and cases in the case base are ranked according to their probability of relevance to the input case. Weights are calculated based on the relevant cases to the input case. For this purpose, the input case is matched against the induced rules. If matched rule(s) classify the input case to a single concept, cases belonging to that concept are considered relevant. If there are multiple matches, where rules classify the input case to different concepts, all cases belonging to those concepts are considered relevant. If no rule fires, rules partially matching the input case are ranked and the relevant cases are the ones belonging to the concept corresponding to the rules with the highest score. The numeric prediction task is mainly a case-based process using rules for weighting and relevance assessment. The classification task employs both RBR and CBR and returns the result of RBR if the input case is classified to a single concept or employs CBR, otherwise it uses the weighting relevance procedures described above. Experimental results comparing the accuracy of ELEM2-CBR with pure case-based methods or decision tree methods demonstrate its effectiveness.

URS-CBR [35] is a system used in Dutch Railways to classify images acquired from ultrasonic rail inspection. The amount of data (images) produced from ultrasonic inspection is huge and comes in a great variety making it necessary to minimize human intervention by performing automatic and reliable classifications. Efficiency, adaptability and maintenance were also prerequisites. Combination of rules with cases solved the problem. The system is made of two rule-based modules and a case-based module. For efficiency and maintenance reasons, cases are organized into a hierarchy of clusters and also the size of the rule bases is kept small. The first rule-based module precedes CBR. It takes as input the given image and tries to classify it. If it is successful in classifying the image, reasoning stops for that image. Otherwise, reasoning passes to the case-based module, which retrieves the most similar cases to the input case. To improve the efficiency of the retrieval process, intermediate conclusions reached by the first rule-based module are exploited for classification of the case to an appropriate cluster. For reliability reasons, the second rule-based module evaluates the retrieved cases in order to match them with the input case. Experiments were carried out comparing the hybrid system with pure rule-based and case-based classifiers. The results for the hybrid system showed an improvement in classification accuracy compared to both other systems. Its inference efficiency was worse than the pure rule-based system but better than the pure case-based system.

The system described in [55] is used for automated sleep stage scoring. The reason for using a hybrid system in that domain is the fact that human experts make decisions based on the combination of rules and experience. Rule-based knowledge is usually incomplete. The system consists of a signal processing unit, a rule-based and a case-based scoring unit. Rules are used to deal with usual situations and cases deal with details and exceptions to the rules. The rule-based module uses a simplified version of the certainty factor called the reliability value. In each reasoning phase, the rule-based scoring unit is first called. If the reliability value of the reached scoring conclusion exceeds a predefined threshold, the scoring process ends without invoking the case-based unit. If there are conflicts in applying rules or if no rule fires or if the reliability value of the reached conclusion is less than the threshold, the reasoning results of the rule-based unit are passed to the case-based unit that is invoked to make the decision. Cases include attributes regarding the applied rules and the conclusions of the rule-based reasoning process. These attributes play a role in similarity assessment. Experimental results showed an improvement in the accuracy of the hybrid system compared to pure rule-based or case-based systems.

In [65], a medical system for oncology is presented. Such a system can be used in hospital units to automate the process of checking whether a patient’s case complies with appropriate guidelines or not. If it does not comply with guidelines, similar patients’ cases will be exploited by experts to reach therapeutic decisions. Rules represent guidelines. A common restricted vocabulary is used for guidelines and cases. Key medical terms in both cases and guidelines are used to select the appropriate guideline with which to compare the case at hand. If the new case does not comply with the selected guideline, the results of RBR are used to determine similar cases to the input case. More specifically, the last guideline step with which the case complies is used to search for similar cases. The system is designed to be a data warehouse.

In [41] an approach for internal audits in banks is presented. Such an approach reduces risks, enables quick decision making for financial incidents and assists in upholding regulations, soundness and integrity of the financial system. Internal audits in banks usually involve time-consuming and tedious paperwork to examine numerous transactions as automatic audit systems are unusual. The approach belongs to conditional sequence subcategory. In the presented approach, RBR is invoked first to automatically detect suspicious transactions for which further actions are necessary. If such transactions are detected, the CBR component is invoked to scrutinize these transactions and provide punishment levels for involved employees. Rules formalize regulations and guidelines that should be upheld by employees. CBR works better than RBR in determining and recommending punishments since judgment is based on intuition and experience.

3.2. Co-processing Approaches

Presentation of representative co-processing approaches is organized in two sections. One section involves cooperation oriented approaches and the other one reconciliation oriented approaches.

3.2.1 Cooperation oriented

We present both types of representative cooperation oriented approaches: approaches employing explicit reasoning control and approaches employing implicit reasoning control. Table 4 depicts the co-processing employing explicit reasoning control and the ones employing implicit reasoning control.

Table 4. Representative cooperation oriented co-processing approaches.

Explicit Reasoning Control	[64], [51]
Implicit Reasoning Control	[9], [10], [11], [66], [34], [12], [31]

3.2.1.1 Explicit reasoning control

The presented cooperation oriented approaches employing explicit reasoning control are [64], [51].

CABARET [64] is an approach performing interpretation tasks in a legal reasoning domain (i.e. income tax law). CABARET consists of two co-reasoners, a rule-based and a case-based (having an equivalent status), a rule-based and a case-based monitor, a controller and a task agenda. The progress of each co-reasoner is observed by its associated monitor. The observations are described in a language understandable by the controller. The controller observes the operation of the whole system and each co-reasoner separately and decides how they will proceed in the reasoning process as a whole and individually. For this purpose, the controller uses a set of domain-independent heuristic rules encoded in the same language as the monitors' observations. Based on those heuristic rules, the controller adds, deletes or orders tasks for each co-reasoner on the agenda. The posted tasks enable the dynamic interleaving of the RBR and CBR processes. CABARET was reimplemented as a blackboard system.

The approach described in [51] integrates rules and cases in an innovative way. The approach has been applied to a medical domain, more specifically to diabetic patient management. The rule base of the system contains different classes of rules corresponding to different steps in the reasoning process. The innovative aspect is the ability to dynamically adapt rules belonging to specific classes in order to improve handling the new situation. Refinement of the rules is performed with the use of cases and involves certain parameters of the rules, which are too general to deal with the specific situation. Such parameters, for instance, are numeric thresholds appearing in conditions. The integration of RBR and CBR is controlled by a supervisor module that contains integration meta-rules. The integration makes the system more effective in detecting the patient's problems and providing enhanced prescriptions, thus reducing the time required to resolve the patient's problems.

3.2.1.2 Implicit reasoning control

The presented cooperation oriented approaches employing implicit reasoning control come from [9], [10], [11], [66], [34], [12] and [31].

CARE-PARTNER [9] proposes a framework for the close combination of the different knowledge base entities. Rules and cases are described using the same knowledge representation language. In this way, during inference, the knowledge base can be searched in parallel for applicable rules and cases enabling the reuse of all knowledge base entities. Pattern matching and case-based retrieval is performed in parallel and the conflict set may simultaneously contain rules as well as cases. Conflict resolution is based on two criteria: similarity to the input case and type of entities. Firstly, the conflict set entities are ranked according to their similarity degree to the input case and the most similar one is chosen. If there are two or more entities having the maximum similarity degree to the input case, a priority order is used giving preference to rules and then to cases. Therefore, the reasoning cycle tightly integrates the different knowledge base entities. This approach has been applied to a medical domain, more specifically to post-transplant patient care. A Web-based system has been developed for this purpose.

GREBE [10], [11] is an approach used in a legal reasoning domain generating arguments for specific point of views. GREBE uses a complex structured case representation scheme. More specifically, a semantic network representation is used to configure relations between case entities. Subgraphs of the graphical case representation relate facts relevant to a court decision concerning the satisfaction of the statutory predicate and those facts are the criterial facts of the case with respect to the predicate. In this way, GREBE's case representation is able to represent the relation between facts and results as determined by the court. The case-based reasoner possesses the mechanisms to efficiently handle the complex case representation. Its main actions are to retrieve the cases whose criterial facts most closely match those of the new case, to determine the best mapping from the criterial facts to the new case and to determine any facts that would improve the match if they were inferred. GREBE tries to solve its goals using both rules and cases providing to the user all the solutions it can find. An innovative reasoning aspect of GREBE is the ability to generate arguments created from parts of different cases and rules. The explanations produced from the synergy of the rule-based and case-based components are processed before shown to the user.

GYMEL [66] is a system for harmonizing melodies. Searching in the case base to find matching melodies proved to be a difficult problem and so each input problem was dealt as a set of simple problems. Each simple problem is to find a chord for a specific position based on information regarding this position and the previous chords in the sequence. If more than one chord is found for a position, backtracking is used to search all possibilities. For the solution of a simple problem, case-based reasoning is first invoked. Rules are invoked when the cases cannot produce a solution at a certain point during inference. The solution proposed by the rule-based module is passed to the case-based module that carries on inference. The approach is useful in application domains for which it is difficult to acquire an adequate set of cases and the CBR component needs to be backed up by a rule-based component expressing general knowledge. In such an approach, the invocation frequency of the rule-based component will be high at the early stages of the system's operation. Subsequently, however, it will decrease, as new cases will be incorporated into the case base.

In [34], an architecture concerning the analysis of event-based dynamic situations is described. Such a system could contribute to the understanding and awareness of complex scenarios such as homeland security threats and future battlespace engagements. The approach combines event correlation/management with situation awareness. More specifically, RBR is used for spatio-temporal event correlation and CBR for situation awareness. The rule-based and case-based modules act in a distributed fashion with each module dynamically invoking the other during inference.

SHYSTER-MYCIN [12] is a hybrid system used in the legal domain of copyright law. It combines SHYSTER, a case-based legal expert system, with MYCIN, a rule-based expert system (Buchanan and Shortliffe 1984). In this integration scheme, MYCIN was altered in a few aspects: its reporting was improved and no certainty factors were used due to the difficulty in defining them in this legal domain. Reasoning in SHYSTER-MYCIN focuses on the rules consulting cases, when an open textured term is met. However, there is no underlying control strategy for the invocation of SHYSTER and evaluation of its results. The system consults the user whether SHYSTER will be called when an open textured term is met or whether he/she can give an answer based on his/her knowledge. If SHYSTER is called, the user passes its reasoning results to MYCIN with the capability to make changes. Also, MYCIN and SHYSTER do not share facts and the user himself/herself has to pass data from one module to the other (the authors mention that a future version of the system will deal with this). Special care has been taken for testing SHYSTER-MYCIN. SHYSTER-MYCIN was tested against three criteria: validity, conciseness and correctness.

In [31] a cooperation-oriented approach in an intelligent Web-based e-learning system is presented. It provides personalized curriculum sequencing, a technology used in Intelligent Tutoring Systems, which involves selection, ordering and construction of the most appropriate teaching material and operations for a specific learner. This is very helpful for each learner because individual learning goals can be achieved more effectively. In contrast to other curriculum sequencing approaches, this approach simultaneously takes more parameters into consideration such as curriculum difficulty level, concept relation degrees of the curriculum, learner test responses in curriculum items, curriculum continuity of successive curriculums. Based on the aforementioned parameters, a genetic algorithm generates personalized curriculum sequencing. A genetic algorithm is useful due to the large search space. CBR performs summative assessment analysis. Summative assessment concerns a large portion of the course (e.g. two or more instruction units). CBR also provides capability to support corrective activities and formative assessment for an individual learner within a specific instruction unit.

3.2.2 Reconciliation oriented

The presented reconciliation oriented approaches come from [23], [40], [3], [5], [19], [58] and [72].

ANAPRON [23] involves combination of independent rules and cases in order to deal with the incompleteness and partial correctness of rules. Rules index cases, supporting them or contradicting them (exception cases), facilitating their retrieval. Exception cases fill the gaps of symbolic rules in representing domain knowledge. Therefore this approach results primarily in accuracy improvement of the rule-based component and secondarily in efficiency improvement of the case-based component. RBR competes with CBR in drawing conclusions. Inference focuses mainly on the symbolic rules, calling CBR only when necessary. The similarity metric of the case-based module returns a similarity score (i.e., a numerical rating of the similarity) and an analogical rule defining implicitly the analogy. During reasoning, firing of a rule is suspended when a sufficient number of its conditions are satisfied and its exception cases are checked. If an exception case is found having compelling analogy with the input case, the rule is not allowed to fire and the conclusion proposed by the retrieved exception case is considered valid instead. Decision regarding compellingness is based on a combination of criteria. More specifically, the similarity score between the exception and the input case, the accuracy and the significance of the analogical rule must exceed predefined thresholds. The accuracy and the significance of the analogical rule is estimated by taking into account both supporting and exception cases indexed by the symbolic rule. ANAPRON has been used in an application field defining the pronunciation of American surnames. This is a difficult task, due to the diverse national origins of the surnames. Experimental results have demonstrated the effectiveness of the combination, since ANAPRON approximates the performance of commercial systems in the domain. CCAR [40] handles inference as ANAPRON with the difference that only exception cases (and not cases supporting rules) are stored in the case base in order to improve case searching efficiency.

CoRCase [3] uses CBR to improve the real-time problem-solving capabilities of RBR used in a classification task. It can be thought of as an extension to the approach used in ANAPRON. Different types of indices are employed for the cases according to all the roles they play in rule-based problem solving. A case that has been solved successfully by the system (i.e., the system outcome is confirmed by the expert) is indexed as true positive by the solution found and as true negative by each rejected solution during problem solving. An erroneously solved case is indexed as false positive by the rule it satisfies and as false negative with respect to the category representing its real solution that has been rejected during problem solving. Indices are used after the invocation of the RBR component to analyze the case at hand and determine similar stored cases. Reconciliation is used to deal with two situations: when there is an indication that the expert will reject the rule-based solution (due to past experience) and when RBR cannot produce a solution to the problem at hand. The conclusion produced by the system corresponds to the best-matched case. The retrieval process takes into account rules as well due to the fact that rules themselves are considered as generalized cases.

In [5] among others, a combination of a neural network and CBR according to the reconciliation coupling approach is presented for accuracy improvement. The case base consists of the neural network training examples and each case is indexed by its real solution and by its neural network solution. The approach can employ any type of neural network performing classification.

MARS [19] is a hybrid system used in the financial domain of mergers and acquisitions. The system achieves a seamless combination of RBR and CBR within one architectural framework, that of RBR. The system uses possibilistic reasoning to represent uncertainty and imprecision underlying the reasoning process. Rules are associated with a sufficiency measure (indicating the strength with which the antecedent implies the consequent), a necessity measure (indicating the degree to which a failed antecedent implies a negated consequent) and a context, which represents the set of preconditions determining the rule’s applicability to a given situation. Cases are implemented as rule templates. To achieve this conversion, information such as sufficiency, necessity and context is needed for each case. CBR is activated at specific situations determined by the system designer. Rules and cases are considered as separate proof paths to a conclusion, making proportional contribution or disconfirmation of the conclusion.

In [58] an approach for lung disease diagnosis is presented. The approach combines a CBR component using fuzzy terms in case representation with a fuzzy RBR component. The case base consists of patient records whereas rules encompass doctor experience. Both modules are invoked in parallel and a type of numeric reconciliation is performed: the similarity value of the most relevant case and the conclusion degree of the fired rule are averaged to produce a more accurate and realistic conclusion degree. Both combined approaches contribute to the diagnosis with the same weight in case they diagnose the same disease. In case they diagnose different diseases, the combination of the components' conclusions cannot be done.

In [72] an approach combining fuzzy CBR with fuzzy RBR is presented. The application domain involves treatment planning for adolescent early intervention of mental healthcare. The specific domain is crucial and complex. Rules represent experience of social service professionals whereas cases client records. The RBR and CBR components are invoked in parallel. The corresponding results are combined according to specific formulas.

3.3 Embedded Processing

As already mentioned, embedded processing approaches give pre-eminence to CBR or pre-eminence to other intelligent method (Figure 2).

Embedded processing approaches giving pre-eminence to CBR involve CBR systems employing one or more modules of other representation methods to perform their internal (offline and online) tasks. Typical such CBR tasks involve retrieval and adaptation. Retrieval concerns several procedures such as situation assessment, employing preferences, exclusion criteria and heuristic procedures in case selection [38]. Adaptation is a time-consuming and complex task often requiring domain-specific knowledge [38], [50]. A single intelligent method (e.g. genetic algorithm or neural network) may be employed in different CBR tasks.

Indicative internal CBR tasks that can be performed by other intelligent methods are the following:

- *Initial case base construction.* In domains with insufficient amount of available cases, intelligent methods such as RBR [54], fuzzy methods [69] and genetic algorithms [68].
- *Maintenance of case base*. Maintenance tasks play a significant role in time-performance and accuracy of a CBR [18], [74]. For such

tasks, intelligent methods such as rules, genetic algorithms (Ahn and Kim 2009), neural networks [49] and fuzzy methods [67] may be employed.

- *Case representation.* For case representation, methods such as genetic algorithms [36], neural networks [49] and fuzzy methods [72] may be used.
- *Case retrieval*. To retrieve useful past cases, various intelligent methods may be used such as RBR [38], fuzzy methods [42], neural networks [79] and genetic algorithms [76].
- *Case adaptation*. To perform case adaptation, methods such as domain-specific and domain-independent rules ([38], [50], [37]), neural networks [22] and genetic algorithms [32].

An embedded approach of this type is DIAL [37]. DIAL is a system developed for disaster response planning and effectively deals with a main problem of case-based systems that is, the acquisition of case adaptation knowledge. The innovative idea of this system is to acquire adaptation knowledge during its operation in the form of cases. Another benefit of case-based adaptation knowledge is its adaptability, in contrast to rule-based adaptation knowledge, enabling the generation of more effective plans. Furthermore, similarity measures are dynamically adapted based on the acquired case-based adaptation knowledge. Multiple cooperating rule-based and case-based components are incorporated into the case-based planner in order to perform the adaptation and similarity tasks. Rule-based adaptation knowledge consists of general abstract rules and rule-based similarity knowledge corresponds to predefined domain-specific criteria. The system tries to perform each task by calling the case-based component falling back on the rule-based component in case of failure. The advantages of the system are the improved inference efficiency and the generation of better plans compared to a conventional case-based system.

Embedded approaches giving pre-eminence to the other intelligent method are less usual however they can be interesting as far as hybridism is concerned. Such implemented approaches mainly involve use of CBR to enhance genetic algorithms.

CBR may improve genetic algorithms in the following ways:

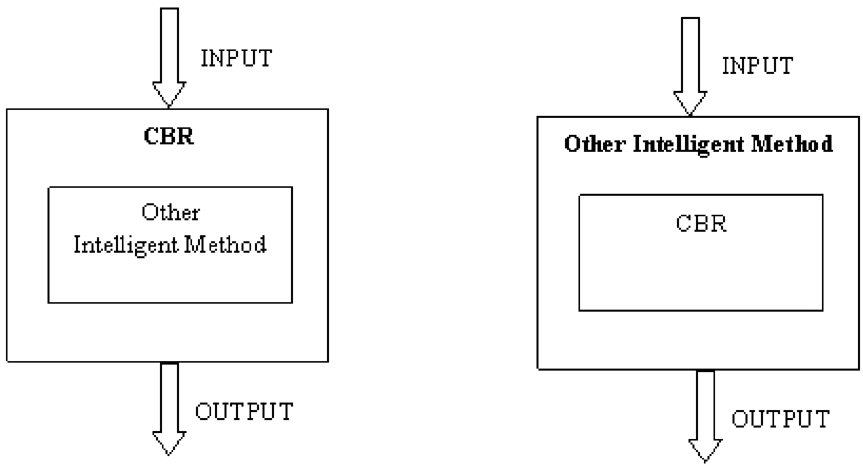

Figure 2. Embedded Processing Model: pre-eminence to CBR (left), pre-eminence to other method (right).

- *Tuning genetic algorithm parameters* such as population size, crossover rate and mutation rate [56]. The values of these parameters play an important role in the performance of a genetic algorithm.
- *Exploiting stored cases to enhance genetic process*. Phases of the genetic process may be appropriately stored as cases and used subsequently as part of the chromosome population [57]. Such approaches may reduce convergence time and improve accuracy of genetic algorithms.
- *Exploiting stored cases for provision of explanations and knowledge extraction* [57]. Genetic algorithms do not provide explanations for reached solutions. Deriving knowledge regarding the genetic algorithm process may be useful to the implementation of future genetic algorithms. Stored cases corresponding to phases of the genetic process may contribute in handling such issues.

Implementation of approaches embedding CBR within other intelligent methods besides genetic algorithms could be an interesting future direction. Such an approach could exploit accumulated experience to improve internal tasks of intelligent methods (e.g. by learning from successes and failures).

4. COMBINATION OF CBR WITH NEURULES

In the following, we describe an approach combining CBR with neurules, a type of hybrid rules integrating symbolic rules with a neural component (i.e. adaline unit) in a uniform/seamless way [59], [28]. The integrated approach belongs to the reconciliation oriented co-processing category.

Neuro-symbolic approaches combine neural and symbolic approaches. A large part of such approaches combine symbolic rules with neural networks. Such combinations have produced effective representation formalisms due to the complementary advantages/disadvantages of the combined approaches [28].

Rules offer a number of advantages for knowledge representation such as, naturalness, modularity, interactive inference mechanisms enabling inference tracing by humans and explanation mechanisms providing explanations regarding inference process. Naturalness facilitates comprehension of knowledge represented by rules whereas modularity refers to the fact that each rule is an autonomous unit. However, rules exhibit certain drawbacks such as difficulty in knowledge acquisition from experts, inability to exploit experience in inference, inference efficiency problems in very large rule bases and inability to draw conclusions in case of missing values in input data or in case of unexpected input values. Neural networks exhibit advantages such as knowledge acquisition from training examples, representation of complex knowledge, efficiency in producing outputs and generalization capabilities. On the other hand, neural networks lack the naturalness and modularity of symbolic rules making it difficult to comprehend their encompassed knowledge, do not provide interactive inference mechanisms and do not provide explanations for reached output.

Most neuro-symbolic approaches resulting into a uniform/seamless combination of the symbolic and neural components give pre-eminence to the neural component. More specifically, the neural component is the main one in which symbolic knowledge is incorporated in or mapped to. In this way, most neuro-symbolic approaches lack the advantages of symbolic rules. In contrast to such approaches, neurules give pre-eminence to the symbolic component retaining naturalness and modularity of symbolic rules and also providing interactive inference mechanisms and explanation facilities [25], [26], [27], [30]. Neurule-based reasoning is more efficient than symbolic RBR [25]. Also in contrast to symbolic rules, conclusions can be reached from neurules even if some of the conditions are unknown. Finally, neurules generalize quite well [30].

4.1 Syntax and Semantics

Neurules are a kind of integrated rules. The form of a neurule is depicted in Fig.3a. Each condition C_i is assigned a number sf_i, called its *significance factor*. Moreover, each rule itself is assigned a number sf_0, called its *bias factor*. Internally, each neurule is considered as an adaline unit (Fig.3b). The *inputs* C_i (i=1,...,n) of the unit are the conditions of the rule. The weights of the unit are the significance factors of the neurule and its bias is the bias factor of the neurule. Each input takes a value from the following set of discrete values: [1 (true), -1 (false), 0 (unknown)].

The *output D*, which represents the conclusion (decision) of the rule, is calculated via the standard formulas:

$$D = f(a), \quad a = sf_0 + \sum_{i=1}^{n} sf_i C_i \tag{1}$$

$$f(a) = \begin{cases} 1 & \text{if } a \geq 0 \\ -1 & \text{otherwise} \end{cases} \tag{2}$$

where ***a*** is the *activation value* and *f(x)* the *activation function*, which is a threshold function. Hence, the output can take one of two values ('-1', '1') representing failure and success of the rule respectively. The significance factor of a condition represents the significance (weight) of the condition in drawing the conclusion.

The general syntax of a neurule (in a BNF notation, where '< >' denotes non-terminal symbols) is:

<rule>::= (<bias-factor>) if <conditions> then <conclusion>
<conditions>::= <condition> | <condition>,<conditions>
<condition>::= <variable> <l-predicate> <value> (<significance-factor>)
<conclusion>::= <variable> <r-predicate> <value> .

where <variable> denotes a *variable*, that is a symbol representing a concept in the domain, e.g. 'sex', 'pain' etc in a medical domain, and <l-predicate> denotes a symbolic or a numeric predicate. The symbolic predicates are {is, isnot}, whereas the numeric predicates are {<, >, =}. <r-predicate> can only be a symbolic predicate. <value> denotes a value; it can be a symbol (e.g. “male”, “night-pain”) or a number (e.g “5”). <bias-factor> and <significance-factor> are (real) numbers.

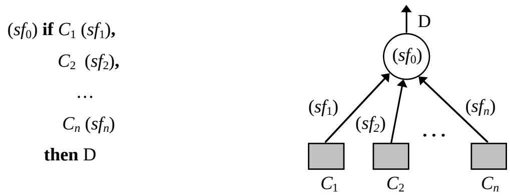

Figure. 3. (a). Form of a neurule, (b) a neurule as an adaline unit.

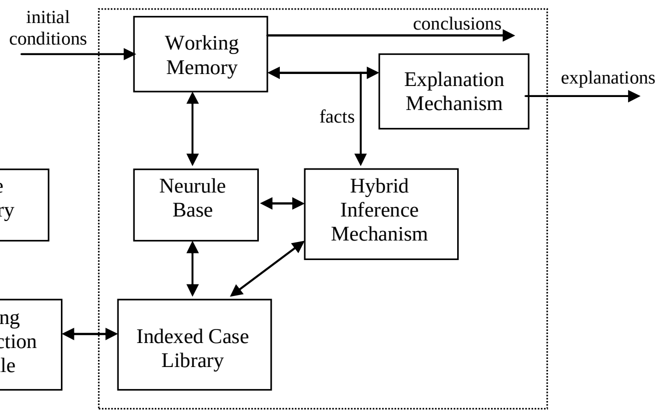

Figure 4. Architecture of a system integrating CBR with neurules.

A variable in a condition can be either an input variable or an intermediate variable or even an output variable, whereas a variable in a conclusion can be either an intermediate or an output variable. An input variable takes values from the user (input data), whereas intermediate or output variables take values through inference since they represent intermediate and final conclusions respectively.

Neurules are constructed either from empirical data (i.e. training examples) [26] or from symbolic rules [25] thus exploiting existing symbolic rule bases. In either creation process, an adaline unit is initially assigned to each of the intermediate and final conclusions. Each unit is individually trained via the Least Mean Square (LMS) algorithm. If the patterns in the training set of a neurule form a non-separable set, special techniques are used. In that case, more than one neurule having the same conclusion are produced. When neurules are produced from symbolic rules, each neurule usually corresponds to (or merges) a set of symbolic rules called its merger set [25]. Therefore, the size of the neurule base is reduced compared to the size of the corresponding symbolic rule base.

The neurule-based inference engine gives pre-eminence to symbolic reasoning, based on a backward chaining strategy [25]. Conclusions are reached based on the values of the condition variables and the weighted sums of the conditions. A neurule fires if the output of the corresponding adaline unit is computed to be ‘1’ after evaluation of its conditions. A neurule is said to be ‘blocked’ if the output of the corresponding adaline unit is computed to be ‘-1’ after evaluation of its conditions. To facilitate inference, conditions of neurules are organized according to the descending order of their significance factors. When a neurule is examined during inference, certain heuristics are applied to avoid evaluation of all its conditions [25].

4.2 Indexing and Hybrid Inference

Figure 4 depicts the architecture of a system integrating neurule-based and case-based reasoning. The run-time system (in the dashed shape) consists of the following modules: the *working memory*, the *hybrid inference mechanism*, the *explanation mechanism*, the *neurule base* and the *indexed case library*. The neurule base contains neurules. Neurules index cases representing their exceptions. The *indexing construction module* implements the process of acquiring an indexing scheme. The indexing process takes as input the following two types of knowledge:

- *Available neurules and cases*. The indexing scheme for this type of knowledge is acquired by performing neurule-based reasoning for the neurules based on the attribute values of each case. Whenever a neurule fires and the value of the conclusion variable does not match the corresponding attribute value of a case, the case is marked as an exception to this neurule.
- *Available symbolic rules and exception cases*. This type of knowledge concerns an available formalism of symbolic rules and

indexed exception cases as the one presented in [23]. The indexing scheme for this type of knowledge is acquired by converting symbolic rules to neurules. The produced neurules are associated with the exception cases of the symbolic rules belonging to their merger sets.

The hybrid inference mechanism combines neurule-based and case-based reasoning by considering facts contained in the working memory, neurules in the neurule base and cases in the indexed case library. More specifically, the hybrid inference process focuses on neurules (i.e. neurule-based reasoning). If an adequate number of the conditions of a neurule are fulfilled so that it can fire, firing of the neurule is suspended and CBR is performed for its indexed exception cases. CBR results are evaluated as in [23] to assess whether the neurule will fire or whether the conclusion proposed by the exception case will be considered valid.

Results have shown the effectiveness of the approach [59], [28]. Cases can be used to fill neurule gaps in representing domain knowledge. Therefore, integration of CBR with neurules primarily improves accuracy of the overall system. Integration results in accuracy improvement regardless the source knowledge type of neurules (i.e. symbolic rules or empirical data) [59], [28], [62]. Furthermore, if the knowledge source of the integrated system concerns an available formalism of symbolic rules and indexed exception cases as the one presented in [23], inference is performed more efficiently [59], [28]. Neurules are a type of hybrid rules and thus one could compare our approach with approaches combining RBR with CBR. The approach combining neurules with CBR offers advantages such as more efficient inferences and drawing of conclusions even if certain input values are unknown.

Due to the fact that neurules seamlessly integrate symbolic rules with a neural component, the specific approach integrates three intelligent methods: symbolic rules, neural networks and CBR. Few (non-embedded) CBR integrations involve more than two combined approaches. Furthermore, the approach offers advantages such as naturalness, modularity, provision of explanations for drawn conclusions and exploitation of different knowledge sources.

It should be mentioned that combinations of neuro-symbolic approaches with CBR are quite rare. Such combinations could be an interesting research direction as they could exploit different types of knowledge sources such as symbolic domain knowledge (usually in the form of rules), training examples and case-based knowledge.

Another approach integrating a neuro-symbolic method with CBR is presented in [4]. Integration follows the reconciliation oriented co-processing approach. The specific neuro-symbolic method concerns a type of knowledge-based neural network. Knowledge-based neural networks are neural networks to which initial symbolic domain knowledge is mapped. The specific approach lacks advantages of our approach such as naturalness, modularity and ability to provide explanations.

An interesting future direction in the integration of CBR with neurules involves use of different types of case indices besides 'exception' indices. Initial results towards this direction are promising [62]. An additional future direction involves maintenance of the integrated representation scheme in case of updates in the neurule source knowledge (i.e. symbolic rule base or training examples). In [60], mechanisms for efficiently updating a neurule base due to changes to its symbolic source knowledge (i.e. symbolic rule base) are presented. Changes to the symbolic rule base involve insertion of a new symbolic rule or removal of an old rule. The presented mechanisms efficiently update the neurule base due to such changes to the source knowledge by storing information related to the neurule construction process to a tree, called the splitting tree. These update mechanisms should be extended and revised to accommodate a formalism integrating CBR with neurules.

5. CONCLUSIONS

In this chapter, we discuss issues involving integrations of CBR with other intelligent methods. Several such approaches have been developed. We categorize CBR integrations, briefly present representative systems applied in various domains and outline directions for future work. We also discuss issues involving combination of CBR with neurules, a neuro-symbolic method retaining advantages of symbolic rules.

CBR integrations concern an important area for AI researchers. Working processes in most fields have been automated with the use of various information systems. Such systems record case data in electronic form. Therefore, an abundant amount of cases is available in several domains. Such data can be exploited in development of integrated intelligent systems when deemed necessary facilitating knowledge acquisition. Research fields involving other combinations (e.g. neuro-symbolic or neuro-fuzzy methods) have been extensively explored. Various types/categories of such combinations have been implemented. This remains to be done for CBR integrations.

REFERENCES

[1] Aamodt, A. & Plaza, E. (1994). Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches. *AI Communications*, *7*, 39-59.

[2] Abraham, A. (2003). Intelligent Systems: Architectures and Perspectives. In J., Kacprzyk, A. Abraham, & L. C. Jain, (Eds.), Recent Advances in Intelligent Paradigms and Applications: *Studies in Fuzziness and Soft Computing*, (1-35). Heidelberg, New York: Physica-Verlag.

[3] Agre, G. (1995). KBS Maintenance as Learning Two-Tiered Domain Representation. In M. Veloso, & A. Aamodt, (Eds.), Case-Based Reasoning Research and Development: *Lecture Notes in Artificial Intelligence*, (*vol. 1010*, 108-120). Berlin, Heidelberg, New York: Springer-Verlag.

[4] Agre, G. & Koprinska, I. (1996). Case-Based Refinement of Knowledge-Based Neural Networks. In J., Albus, A. Meystel, & R. Quintero, (Eds.), Proceedings of the International Conference "Intelligent Systems: A Semiotic Perspective" (vol. II: *Applied Semiotics*, 221-226), Gaithersburg, MD: US Government Printing Office.

[5] Agre, G. (1998). A Two-Tiered Reasoning and Learning Architecture. *In Proceedings of the 1998 AAAI Spring Symposium on Multimodal Reasoning*, AAAI Technical Report SS-98-04 (124-129), Menlo Park, CA: AAAI Press.

[6] D. Aha, & J. J. Daniels, (Eds.) (1998). Case-Based Reasoning Integrations: Papers from the 1998 AAAI Workshop. *Technical Report*, WS-98-15. Menlo Park, CA: AAAI Press.

[7] Bader, S. & Hitzler, P. (2005). Dimensions of Neural-Symbolic Integration – a Structured Survey. In S., Artemov, H., Barringer, A. S., D'Avila Garcez, L. C. Lamb, & J. Woods, (Eds.), We Will Show Them: Essays in Honour of Dov Gabbay (volume 1, 167-194). *International Federation for Computational Logic*, College Publications.

[8] Balducelli, C. & D' Esposito, C. (2000). Genetic Agents in an EDSS

System to Optimize Resources Management and Risk Object Evacuation. *Safety Science*, *35*, 59-73.

[9] Bichindaritz, I., Moinpour, C., Donaldson, G., Bush, N., Kansu, E. & Sullivan, K. M. (2003). Case-Based Reasoning for Medical Decision-Support in a Safety Critical Environment. In M., Dojat, E. Keravnou, & P. Barahona, (Eds.), Artificial Intelligence in Medicine Europe: *Lecture Notes in Artificial Intelligence*, (*vol. 2780*, 314-323). Berlin, Heidelberg, New York: Springer-Verlag.

[10] Branting, L. K. (1991). Building Explanations from Rules and Structured Cases. *International Journal of Man-Machine Studies*, *34*, 797-837.

[11] Branting, L. K. (2003). A Reduction-Graph Model of Precedent in Legal Analysis. *Artificial Intelligence*, *150*, 59-95.

[12] O'Callaghan, T. A., Popple, J. & Mc Creath, E. (2003). SHYSTER-MYCIN: A Hybrid Legal Expert System, *in Proceedings of the Ninth International Conference on AI in Law*, (103-104), New York, NY: ACM Press.

[13] Cercone, N., An, A. & Chan, C. (1999). Rule-Induction and Case-Based Reasoning: Hybrid Architectures Appear Advantageous. *IEEE Transactions on Knowledge and Data Engineering*, *11*, 164-174.

[14] Cheetam, W., Shiu, S. C. K. & Weber, R. O. (2006). Soft Case-Based Reasoning. *Knowledge Engineering Review*, *20*, 267-269.

[15] Chen, J. H. & Hsu, S. C. (2007). Hybrid ANN-CBR Model for Disputed Change Orders in Construction Projects. *Automation in Construction*, *17*, 56–64.

[16] Chen, H. P. & Wilkinson, L. J. (1998). *Case Match Reduction through the Integration of Rule-based and Case-Based Reasoning Procedures*. In [6] (33-38).

[17] Chi, R. T. H. & Kiang, M. Y. (1993). Reasoning by Coordination: an Integration of Case-Based and Rule-Based Reasoning Systems. *Knowledge-Based Systems*, *6*, 103-113.

[18] De Mantaras, R. L., McSherry, D., Bridge, D., Leake, D., Smyth, B., Craw, S., Faltings, B., Maher, M. L., Cox, M. T., Forbus, K., Keane, M., Aamodt, A. & Watson, I. (2005). Retrieval, Reuse, Revision, and Retention in Case-Based Reasoning. *The Knowledge Engineering Review*, *20*, 215-240.

[19] Dutta, S. & Bonissone, P. P. (1993). Integrating Case Based and Rule Based Reasoning. *International Journal of Approximate Reasoning, 8*, 163-203.

[20] Dzeng, R. J. & Lee, H. Y. (2004). Critiquing Contractors' Scheduling by Integrating Rule-Based and Case-Based Reasoning. *Automation in Construction*, *13*, 665-678.

[21] Evans-Romaine, K. & Marling, C. (2003). Prescribing Exercise Regimens for Cardiac and Pulmonary Disease Patients with CBR. In Proceedings of Workshop on CBR in the Health Services, 5th *International Conference on Case-Based Reasoning*, (45-52).

[22] Fdez-Riverola, F. & Corchado, J. M. (2004). FSfRT: Forecasting System for Red Tides. *Applied Intelligence*, *21*, 251-264.

[23] Golding, A. R. & Rosenbloom, P. S. (1996). Improving Accuracy by Combining Rule-Based and Case-Based Reasoning. *Artificial Intelligence*, *87*, 215-254.

[24] Hanemann, A. & Marcu, P. (2008). Algorithm Design and Application of Service-Oriented Event Correlation. *In Proceedings of the 3rd IEEE/IFIP International Workshop on Business-driven IT Management*, (61-70). IEEE.

[25] Hatzilygeroudis, I. & Prentzas, J. (2000). Improving the Performance of Symbolic Rules. *International Journal on Artificial Intelligence Tools*, *9*, 113-130.

[26] Hatzilygeroudis, I. & Prentzas, J. (2001a). Constructing Modular Hybrid Rule Bases for Expert Systems. *International Journal on Artificial Intelligence Tools*, *10*, 87-105.

[27] Hatzilygeroudis, I. & Prentzas, J. (2001b). An Efficient Hybrid Rule-Based Inference Engine with Explanation Capability. In J. Kolen, & I. Russell, (Eds.), *Proceedings of the Fourteenth International Florida Artificial Intelligence Research Society Conference*, (227-231). Menlo Park, CA: AAAI Press.

[28] Hatzilygeroudis, I. & Prentzas, J. (2004a). Integrating (Rules, Neural Networks) and Cases for Knowledge Representation and Reasoning in Expert Systems. *Expert Systems with Applications*, *27*, 63-75.

[29] Hatzilygeroudis, I. & Prentzas, J. (2004b). Neuro-Symbolic Approaches for Knowledge Representation in Expert Systems. *International Journal of Hybrid Intelligent Systems*, *1*, 111-126.

[30] Hatzilygeroudis, I. & Prentzas, J. (2010). Integrated Rule Based Learning and Inference. *IEEE Transactions on Knowledge and Data Engineering*, (in press).

[31] Huang, M. J., Huang, H. S. & Chen, M. Y. (2007). Constructing a Personalized E-learning System Based on Genetic Algorithm and Case-Based Reasoning Approach. *Expert Systems with Applications*, *33*, 551–

564.

[32] Huang, B. W., Shih, M. L., Chiu, N. H., Hu, W. Y. & Chiu, C. (2009). Price Information Evaluation and Prediction for Broiler using Adapted Case-Based Reasoning Approach. *Expert Systems with Applications*, *36*, 1014-1019.

[33] Jacobo, V. H., Ortiz, A., Cerrud, Y. & Schouwenaars, R. (2007). Hybrid Expert System for the Failure Analysis of Mechanical Elements. *Engineering Failure Analysis*, *14*, 1435-1443.

[34] Jakobson, G., Buford, J. & Lewis, L. (2004). Towards an Architecture for Reasoning about Complex Event-Based Dynamic Situations. In Proceedings of the Third International Workshop on Distributed Event Based Systems, *in conjunction with the 26th International Conference on Software Engineering*, (62-67), IEE.

[35] Jarmulak, J., Kerckhoffs, E. J. H. & Van't Veen, P. P. (2001). Case-based Reasoning for Interpretation of Data from Non-Destructive Testing. *Engineering Applications of Artificial Intelligence*, *14*, 401-417.

[36] Kim, K. J. (2004). Toward Global Optimization of Case-Based Reasoning Systems for Financial Forecasting. *Applied Intelligence*, *21*, 239-249.

[37] Kinley, L. (2001). Learning to Improve Case Adaptation. PhD Thesis, *Computer Science Department*, Indiana University, USA.

[38] Kolodner, J. L. (1993). *Case-Based Reasoning*. San Mateo, CA: Morgan Kaufmann.

[39] D. B. Leake, (Ed.) (1996). Case-Based Reasoning: Experiences, Lessons, and Future Directions. *Menlo Park*, CA: AAAI Press.

[40] Lee, M. R. (2002). An Exception Handling of Rule-Based Reasoning Using Case-Based Reasoning. *Journal of Intelligent and Robotic Systems*, *35*, 327-338.

[41] Lee, G. H. (2008). Rule-Based and Case-Based Reasoning Approach for Internal Audit of Bank. *Knowledge-Based Systems*, *21*, 140-147.

[42] Li, S. T. & Ho, H. F. (2009). Predicting Financial Activity with Evolutionary Fuzzy Case-Based Reasoning, *Expert Systems with Applications*, *36*, 411-422.

[43] Liu, K. F. R. & Yu, C. W. (2009). Integrating Case-Based and Fuzzy Reasoning to Qualitatively Predict Risk in an Environmental Impact Assessment Review. *Environmental Modelling & Software*, *24*, 1241-1251.

[44] Looney, C. G. & Liang, L. R. (2003). Cognitive Situation and Threat Assessments of Ground Battlespaces. *Information Fusion*, *4*, 297-308.

[45] Marling, C., Petot, G. J. & Sterling, L. S. (1999). Integrating Case-Based and Rule-Based Reasoning to Meet Multiple Design Constraints. *Computational Intelligence*, *15*, 308-332.

[46] Marling, C., Rissland, E. & Aamodt, A. (2006). Integrations with Case-Based Reasoning. *Knowledge Engineering Review*, *20*, 241-245.

[47] Marling, C., Sqalli, M., Rissland, E., Munoz-Avila, H. & Aha, D. (2002). Case-Based Reasoning Integrations. *AI Magazine*, *23*, 69-86.

[48] Marling, C. & Whitehouse, P. (2001). Case-Based Reasoning in the Care of Alzheimer's Disease Patients. In D. Aha, & I. Watson, (Eds.), Case-Based Reasoning Research and Development: *Lecture Notes in Computer Science*, (vol. 2080, 702-715). Berlin, Heidelberg, New York: Springer-Verlag.

[49] Medsker, L. R. (1998). Hybrid Intelligent Systems (Second Printing). Norwell, MA: Kluwer Academic Publishers.

[50] Mitra, R. & Basak, J. (2005). Methods of Case Adaptation: *a Survey*. *International Journal of Intelligent Systems*, *20*, 627-645.

[51] Montani, S. & Bellazzi, R. (2002). Supporting Decisions in Medical Applications: the Knowledge Management Perspective. *International Journal of Medical Informatics*, *68*, 79-90.

[52] Nauck, D., Klawonn, F. & Kruse, R. (1997). *Foundations of Neuro-Fuzzy Systems*. New York, NY: John Wiley & Sons.

[53] Pal, S. K. & Shiu, S. C. K. (2004). *Foundations of Soft Case-Based Reasoning*. New York, NY: John Wiley & Sons.

[54] Pandey, B. & Mishra, R. B. (2009). An Integrated Intelligent Computing Model for the Interpretation of EMG Based Neuromuscular Diseases. *Expert Systems with Applications*, *36*, 9201-9213.

[55] Park, H. J., Oh, J. S., Jeong, D. U. & Park, K. S. (2000). Automated Sleep Stage Scoring Using Hybrid Rule- and Case-Based Reasoning. *Computers and Biomedical Research*, *33*, 330-349.

[56] Pavon, R., Dvaz, F., Laza, R. & Luzon, V. (2009). Automatic Parameter Tuning with a Bayesian Case-Based Reasoning System. A Case of Study. *Expert Systems with Applications*, *36*, 3407-3420.

[57] Perez, E. I., Coello Coello, C. A. & Hernandez-Aguirre, A. (2005). Extraction and Reuse of Design Patterns from Genetic Algorithms using Case-Based Reasoning. *Soft Computing*, *9*, 44-53.

[58] Phuong, N. H., Prasad, N. R., Hung, D. H. & Drake, J. T. (2001). Approach to Combining Case Based Reasoning with Rule Based Reasoning for Lung Disease Diagnosis. *In Proceedings of the Joint Ninth International Fuzzy Systems Association World Congress and*

Twentieth International Conference of the North American Fuzzy Information Processing Society, (vol. 2, 883-888), IEEE.

[59] Prentzas, J. & Hatzilygeroudis, I. (2002). Integrating Hybrid Rule-based with Case-Based Reasoning. In S. Craw, & A. D. Preece, (Eds.), Advances in Case-Based Reasoning, *Lecture Notes in Computer Science*, (vol. 2416, 336-349). Berlin, Heidelberg, New York: Springer-Verlag.

[60] Prentzas, J. & Hatzilygeroudis, I. (2005). Rule-based Update Methods for a Hybrid Rule Base. *Data and Knowledge Engineering*, *55*, 103-128.

[61] Prentzas, J. & Hatzilygeroudis, I. (2007). Categorizing Approaches Combining Rule-Based and Case-Based Reasoning. *Expert Systems*, *24*, 97-122.

[62] Prentzas, J., Hatzilygeroudis, I. & Michail, O. (2008). Improving the Accuracy of Neuro-Symbolic Rules with Case-Based Reasoning. In I., Hatzilygeroudis, C. Koutsojannis, & V. Palade, (Eds.), *Proceedings of the First International Workshop on Combinations of Intelligent Methods and Applications in conjunction with 18th European Conference on Artificial Intelligence*, (49-54), Patras, Greece.

[63] Prentzas, J. & Hatzilygeroudis, I. (2009). Combinations of Case-Based Reasoning with Other Intelligent Methods. *International Journal of Hybrid Intelligent Systems*, *6*, 189-209.

[64] Rissland, E. L. & Skalak, D. B. (1991). CABARET: Rule Interpretation in a Hybrid Architecture. *International Journal of Man-Machine Studies*, *34*, 839-887.

[65] Rossille, D., Laurent, J. F. & Burgun, A. (2005). Modeling a Decision-Support System for Oncology Using a Rule-Based and Case-Based Reasoning Methodologies. *International Journal of Medical Informatics*, *74*, 299-306.

[66] Sabater, J., Arcos, J. L. & Lopez De Mantaras, R. (1998). *Using Rules to Support Case-Based Reasoning for Harmonizing Melodies*, In [6] (147-151).

[67] Shiu, S. C. K., Li, Y. & Wang, X. Z. (2001). Using Fuzzy Integral to Model Case-Base Competence. In Proceedings of the Workshop on Soft Computing in Case-Based Reasoning, *Fourth International Conference in Case-Based Reasoning*, (206-212).

[68] Soh, L. K. & Tsatsoulis, C. (2001). Combining Genetic Algorithms and Case-Based Reasoning for Genetic Learning of a Casebase: A Conceptual Framework. *In Proceedings of the Genetic and Evolutionary Computation Conference*, (376-383). San Mateo, CA: Morgan

Kaufmann Publishers.

[69] Sun, Z., Finnie, G. & Weber, K. (2004). Case Base Building with Similarity Relations. *Information Sciences*, *165*, 21-43.

[70] Surma, J. & Vanhoof, K. (1998). *An Empirical Study on Combining Instance-Based and Rule-Based Classifiers. In*, [6] (130-134).

[71] Vafaie, H. & Cecere, C. (2005). CORMS AI: Decision Support System for Monitoring US Maritime Environment. In N. Jacobstein, B. Porter, (Eds.), *Proceedings of the Seventeenth Innovative Applications of Artificial Intelligence Conference*, (1499-1506). Menlo Park, CA: AAAI Press.

[72] Wang, W. M., Cheung, C. F., Lee, W. B. & Kwok, S. K. (2007). Knowledge-Based Treatment Planning for Adolescent Early Intervention of Mental Healthcare: a Hybrid Case-Based Reasoning Approach, *Expert Systems*, *24*, 232-251.

[73] Watson, I. (1997). Case-Based Reasoning is a Methodology not a Technology. *Knowledge-Based Systems*, *12*, 303-308.

[74] Wilson, D. & Leake, D. (2001). Maintaining Case-Based Reasoners: Dimensions and Directions. *Computational Intelligence*, *17*, 196-213.

[75] Wylie, R., Orchard, R., Halasz, M. & Dube, F. (1997). IDS: Improving Aircraft Fleet Maintenance. In T. Senator, & B. Buchanan, (Eds.), *Proceedings of the Ninth Conference on Innovative Applications of Artificial Intelligence*, (1078-1085). Menlo Park, CA: AAAI Press.

[76] Yuan, F. C. & C. Chiu, C. (2009). A Hierarchical Design of Case-Based Reasoning in the Balanced Scorecard Application. *Expert Systems with Applications*, *36*, 333-342.

[77] Zeleznikow, J., Vossos, G. & Hunter, D. (1994). The IKBALS Project: Multi-Modal Reasoning in Legal Knowledge Based Systems. *Artificial Intelligence and Law*, *2*, 169-203.

[78] Zhou, J., Messermith, C. G. & Harrington, J. D. (2005). HIDES: A Computer-Based Herbicide Injury Diagnostic Expert System. *Weed Technology*, *19*, 486-491.

[79] Zhuang, Z. Y., Churilov, L., Burstein, F. & Sikaris, K. (2009). Combining Data Mining and Case-Based Reasoning for Intelligent Decision Support for Pathology Ordering by General Practitioners. *European Journal of Operational Research*, *195*, 662-675.