

Enhancing Similarity Measures and Context Provision for the Intelligent Monitoring of Business Processes in CBR-WIMS

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Abstract. Business processes have a key role in operating, controlling, and managing large modern organizations. Managing business processes presents a challenge related to the temporal complexity, uncertainty and large volume of data generated. This paper presents new developments and evaluation of an enhanced approach for the intelligent monitoring of business processes using Case-Based Reasoning in the CBR-WIMS platform. A short overview of the CBR-WIMS approach, based on the representation of business process cases as graphs, comprising process events and their temporal relationships is presented. The enhanced similarity measure based on the Maximum Common Sub-graph is presented and an evaluation of its effectiveness and efficiency is shown and discussed. The evaluation uses historical data from a real business process. The paper also discusses the use of a clustering technique in CBR-WIMS. This allows the semi-automatic tagging of cases and so provides enhanced explanation and context to users, increasing the confidence and usability of retrieved solutions and advice. A set of experiments are presented and discussed showing the added value that this enhancement brings to the intelligent monitoring and management of real business processes in an organisation.

Keywords: Case Based Reasoning, Business Workflows, Temporal Reasoning, Graph Similarity, Explanation

1 Introduction

Business processes are an essential part of modern organisations. These are increasingly defined, orchestrated and captured by enterprise software systems operating within the organisation or in many cases across the boundaries of organisations. This provides new opportunities and challenges in terms of building intelligent software systems that support “owners” and managers of business processes in their effort to monitor and manage effectively the operation of business processes they are responsible for.

Business processes are normally represented as a set of activities with temporal relationships and constraints imposed on them. Over the last years software systems have been used increasingly to manage and automate the operation of business processes. This caused a need for a standard formalism to represent business processes. As a consequence, new standards have emerged to fulfil this need. The Business Process Modelling Notation (BPMN) developed by the Business Process Management Initiative (BPMI) and Object Management Group (OMG) provides a standard for the graphical representation of workflow based business processes [1]. Standards cover the definition, orchestration and choreography of business process. A number of such standards have emerged and are widely supported by mainly Service Oriented Architecture (SOA) based enterprise technologies and systems. The OASIS Business Process Execution Language (BPEL), short for Web Services BPEL (WS-BPEL) is a key orchestration technology [2]. The Workflow Management Coalition (WfMC) backed XML Process Definition Language (XPDL) is a format standardised to interchange Business Process definitions between different workflow products and systems [3].

The real challenge that a Business Process faces is the effective monitoring and interpretation of the events that take place. Managers are usually monitoring a number of different business processes, involving different systems, staff as well as actors external to the organisation (such as customers, staff in other organisations and/or systems external to the organisation).

An additional challenge is that systems monitoring a business process may not capture all the information required to understand and make effective decisions for intervention if these are required. This is particularly the

case for a lot of human to human interactions and contextual information that may not be captured by the business process monitoring systems. Additionally, business processes evolve over time and parts of a business processes can be manual overridden by managers, not necessarily providing a rationale for such actions. Overall, this adds a layer of uncertainty that needs to be dealt by any approach that attempts to automatically monitor the business process [4].

Finally, another challenge associated with the production of an efficient intelligent monitoring system is this of explaining the relevance of contextual knowledge and providing an insight in the reasoning process so that managers can have a better understanding and confidence in the monitoring system and any advice offered by such a system. This has particular implications when Case-Based Reasoning (CBR) is used as any retrieved similar cases need to explained in terms of the similarity criteria and relevance of the associated retrieved advice for a particular problem context [5].

This paper presents recent enhancements and evaluation of a CBR approach to the intelligent monitoring of business processes based on past experiential knowledge. CBR-WIMS is a software platform that is used for the specification and integrated intelligent monitoring of business workflows. Section 2 gives some background on business workflow monitoring and an overview of the approach taken in CBR-WIMS. Section 3 presents the business process case study that is used as an experimental vehicle for this research. Section 4 presents the enhanced similarity measures proposed and evaluated in this work and section 5 presents an approach to providing useful context to users to gain a more detailed insight into the retrieved knowledge and advice that CBR-WIMS provides to the business process manager including an evaluation of this approach. The Conclusion summarises the work done and indicates future work currently planned.

2 Approaches to the Monitoring Business Process Workflows

Various approaches to the problem of monitoring a business process have been proposed. When monitoring information about a business process, the current workflow state must be analysed and compared using domain/model knowledge and knowledge gained from past experience. As problems usually recur, if similar cases are found this can provide the context for reasoning about the business process operation or, if no such precedent can be found, new knowledge can be derived in the form of a new case that can be stored in the system for later use. This approach matches the behaviour and process of Case-Based Reasoning (CBR) systems. The standard CBR process cycle follows the Retrieve, Reuse, Revise, Retain model [6]. CBR based systems can be used for this purpose. Literature shows several examples of the effective use of CBR to the management of business workflows. An approach to reuse and adaptation of workflows was proposed by Minor et al [7] where the workflows were represented in terms of graphs and structural similarity measures were applied. Kyong Joo Oh and Tae Yoon Kim [8] have proposed CBR for financial market monitoring and examine whether they can build efficiently the daily financial condition indicator. Dijkman et al[9] have investigated algorithms for defining similarities between business processes focused on tasks and control flow relationships between tasks. Van der Aalst et al [10] compare process models based on observed behaviour in the context of Petri nets. A business process is tightly dependent on its workflow representation which is usually in structural, usually represented in terms of a graph. The definition of similarity measures for structured representations of cases in CBR has been proposed [11] and applied to many real life applications requiring reuse of domain knowledge associated with rich structure based cases [12],[13].

Although CBR seems to be an effective way of monitoring business processes, there is lack of a generic platform which could be abstract enough to host monitoring for an existing business processes and adapt its environment according to the investigated process's needs. An interesting approach which tries to generalize towards implementation of processes using Case Base Reasoning is jColibri [14]; an open-source CBR framework towards integrated applications that specific case knowledge is needed and contain models of general domain knowledge. Another worth mentionable approach is myCBR [15], also open – source CBR tool for rapid prototyping of CBR applications and more specialized on case-based product recommender systems. Both tools work well towards CBR modelling of an application but do not yet offer the possibility of working with business processes defined in terms of a workflow and deal with uncertainty in both definition and operational data.

A CBR approach for the intelligent monitoring of business process workflows has been proposed and has shown able to monitor effectively real business workflows when compared to human domain experts[5],[16]. This approach can deal effectively with the workflow monitoring problem if similarity measures have been defined and known problems from the past have been used in order to form a knowledge case base. Cases based on business process's attributes (events, actions and their temporal relationship) are being represented in terms of a simple graph which is used for estimating similarity.

2.1 The CBR-WIMS approach

In CBR-WIMS business process workflows are defined using UML activity diagrams and mapped through Business Process Management Notation (BPMN)[17] into Web-Services Business Process Execution Language (WS-BPEL) [1] and stored within the system. Business process cases are defined using a graph representation of workflow processes and similarity measures used include summing the similarity between events of a similar nature occurring in business process workflow cases and using an exhaustive graph similarity search algorithm based on the Maximum Common Subgraph [16].

The representation of events in the workflow event log uses a general time theory, based on intervals [18]. In the theory defined here, the temporal relationships have been reduced from the ones proposed by Allen [19] to just one, the “meets” relationship.

The general time theory takes both points and intervals as primitive. It consists of a triad (T , **Meets**, **Dur**), where:

- T is a non-empty set of time elements;
- **Meets** is a binary order relation over T ;
- **Dur** is a function from T to R_0^+ , the set of non-negative real numbers.

A time element t is called an interval if $Dur(t) > 0$; otherwise, t is called a point.

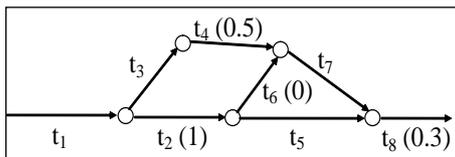
This approach has been shown to be suitable for defining temporal similarity measures in the context of a CBR system based on the graph representation of events and intervals and their temporal relationships and similarity measures based on graph matching techniques such as the Maximum Common Subgraph (MCSG)[12][13]. Additionally, such a graph can be checked for consistency of temporal references using linear programming techniques [20][21].

For example, consider a scenario with a temporal reference (T , M , D), where:

$$T = \{t_1, t_2, t_3, t_4, t_5, t_6, t_7, t_8, t_9\};$$

$$M = \{\text{Meets}(t_1, t_2), \text{Meets}(t_1, t_3), \text{Meets}(t_2, t_5), \\ \text{Meets}(t_2, t_6), \text{Meets}(t_3, t_4), \text{Meets}(t_4, t_7), \\ \text{Meets}(t_5, t_8), \text{Meets}(t_6, t_7), \text{Meets}(t_7, t_8)\};$$

$$D = \{\text{Dur}(t_2) = 1, \text{Dur}(t_4) = 0.5, \text{Dur}(t_6) = 0, \text{Dur}(t_8) = 0.3\}$$



The graphical representation of temporal reference (T , M , D) is shown in Fig. 1:

Fig. 1. Graph representation of temporal relationships

When all events produced by the workflow event log are time stamped there is no uncertainty in the representation of the business process execution and any branches in the timeline showing concurrently occurring parts of the business process can be collapsed into a single timeline of execution. In this case, the similarity measure is easier and faster to calculate as the MCSG is a common segment made up of events and intervals in a given order in each of the compared workflow logs. In this common graph segment each edge (event or interval) has a similarity measure to its counterpart in the other log that exceeds a given threshold value ϵ . Eq. 1 above can still be used to provide the overall similarity between the two workflows. However, other branches of the graph can represent contextual temporal information necessary for the interpretation of a sequence of events, possibly with some uncertainty involved in their exact timing. An example of this is a statement such as: “some time last week I saw John and we agreed to sign off task X”. Other temporal information that could be captured and used for the reasoning could be the proximity to a deadline, or reminder communications broadcast to staff by managers outside the system (i.e. using telephone, or direct email not captured by the system).

Initial experiments using historical data from a real business process has shown that the CBR approach can be quite effective in classifying correctly unknown cases, when compared to a human expert[16].

3 The Exam Moderation Case Study Business Process

In order to evaluate the approach proposed in this research, we used the University of Greenwich, School of Computing and Mathematical Science exam moderation system. This is an automated web enabled secure system that allows various actors to interact with the system as well as among them. These actors can be course (module) coordinators, course moderators, exam drafters (typically senior managers), admin staff and external examiners and can upload, modify, approve and lock student exam papers. The system automates the whole process and provides an audit trail of events generated by workflow stakeholders and the system. The system orchestrates a formal process made up of workflows. The process can be defined and displayed formally in terms of a UML activity diagram (Fig. 2). The system tracks most workflow actions in terms of timed events. Most of these generate targeted email communications to workflow stakeholders, some for information and others requiring specific further actions from these stakeholders.

For example, the action of a new exam version upload from a course coordinator is notified to the moderator, drafter and admin staff. This can prompt the moderator to approve the uploaded version or upload a new version. However, the coordinator can also upload a new version and admin staff may also decide to format the uploaded version and upload it as a newer version. The system captures all versions, workflow actions, emails sent and there is a facility to record free form comments to document versions and/or workflow actions.

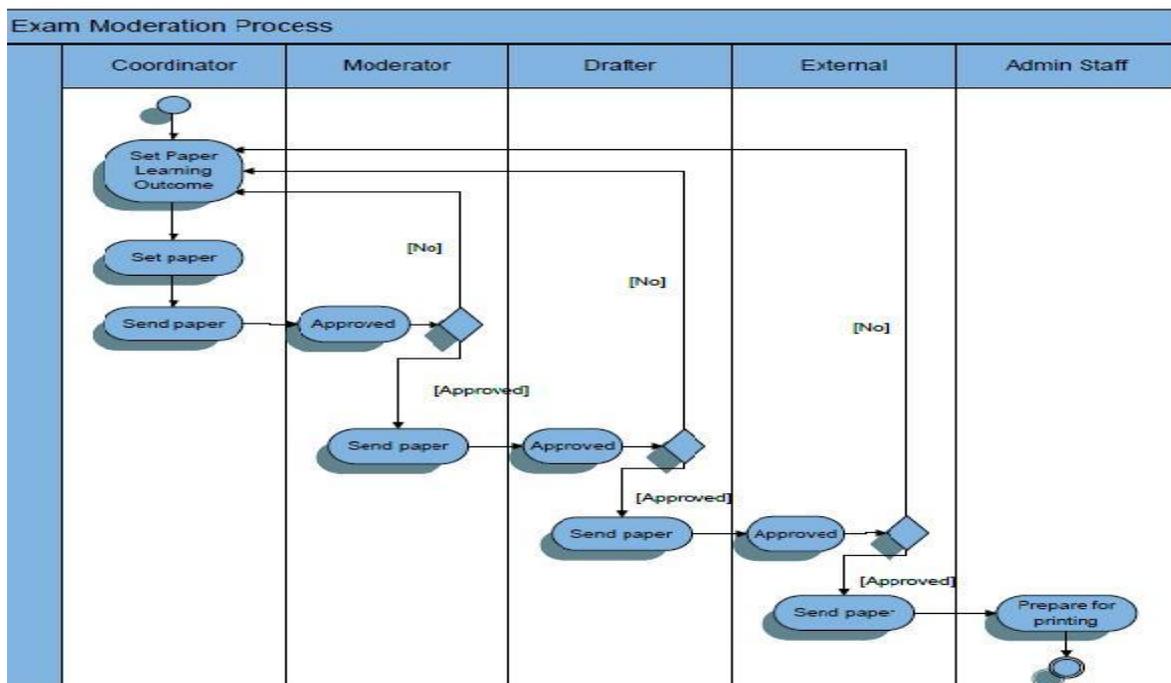


Fig. 2. The exam moderation process activities and workflows (simplified)

Figure 3 shows an example of a real execution of an exam moderation business process. The information from these logs over 4 years of operation with an average of 120 complete business process trails every year are imported in CBR-WIMS through a purpose constructed data adaptor. This is used to provide the case base used in the standard CBR process.

AUDIT TRAIL
Examination document Exam_COMPXX70_ver1_May_2009.DOC has been uploaded by Michael Peterson at 03/04/2009 12:21:43. Email sent to Moderator: mcXX Office: cms-exams
Examination document Exam_MS_COMPXX70_ver1_May_2009.DOCX has been uploaded by Michael Peterson at 04/04/2009 00:06:03. Email sent to Moderator: mcXX Office: cms-exams
Examination document Exam_COMPXX70_ver4_May_2009.DOCX has been uploaded by Ch&&&&g XX at 07/04/2009 13:15:22. Email sent to Coordinator: pmXX Office: cms-exams Head of Department: pmXX
Examination comment has been added by Ch&&&&g Ma at 07/04/2009 13:18:32. Email sent to Coordinator: pmXX Office: cms-exams Head of Department: pmXX
Moderator C&&&&g XX has signed off the Exam and Marking Scheme at 08/04/2009 00:07:17. No Emails sent
Drafter SxTx McKXXie has removed the Moderator Sign Off for the Exam and Marking Scheme at 08/04/2009 11:40:49. Email sent to Moderator: mcXX Coordinator: pmXX Office: cms-exams Head of Department: pmXX

Fig. 3. An example excerpt of an event log showing for the exam moderation process (partially obfuscated)

4 Enhanced similarity measures

Earlier work using CBR-WIMS [16] was based on a combination of two similarity measures:

1. A simple count of similar type events occurring in each business process:

$$\sigma(C, C') = \sum_{i=1}^{no\ of\ event\ types} \frac{N_i^2}{N_{total} \times N'_{total}} \quad (1)$$

Where N_i is the number of events of type i common to both business processes and N_{total} and N'_{total} are the total number of events in business workflow C or C'

2. The Maximum Common Subgraph (MCS) present in both business processes.

The MCS similarity between two such graphs can be defined as:

$$S(G, G') = \frac{\left(\sum_{\substack{\text{matches} \\ C, C' \\ \text{in} \\ MCSG}} \sigma(C, C') \right)^2}{count(G).count(G')} \quad (2)$$

where $count(G)$ represents the number of edges in graph G and $\sigma(C, C')$ is the similarity measure, $0 \leq \sigma(C, C') \leq 1$, between two individual edges (intervals or events) C and C' .

The MCS is calculated using a greedy algorithm that returns the largest connected common subgraph based on a minimum similarity threshold between events and intervals present in both graphs.

Although these measures have shown that they can provide a good prediction of problems with the operation of the business process [16] it was felt that perhaps the fact the algorithm only provides the maximum connected sub-graph present in both graphs it may ignore smaller non overlapping sub-graphs also present in both graphs that may also contain useful similarity information that may be needed in the CBR process.

To investigate this, a second algorithm was developed that returns a set of unconnected and non-overlapping sub-graphs. This has been achieved by changing the stopping criteria of the original algorithm so that once the

MCS is returned, the algorithm is run again on any remaining unmatched segments of the graphs representing the two business processes that are compared for similarity. The final outcome of the similarity measuring algorithm is the highest combination of similar and non-overlapping individual subgraphs of the two business process operations cases compared.

The measure of the overall similarity is still represented by the formula in equation 2 above, but in this case the MCS is not necessarily a connected one. An obvious consequence of this approach is that the similarity measures are now larger than before.

A set of experiments were conducted to establish if using the enhanced similarity measure and algorithm has a beneficial effect on the predictive accuracy of the CBR process and to establish the magnitude of the extra computational overhead needed for the more exhaustive MCS search required by the algorithm.

The set of experiments used in previous work [16] using the exam moderation data was repeated using the enhanced similarity measure. The evaluation involved looking at all events for each exam moderation process. This was a total of 1588 events involving 116 exam moderation workflow processes from one academic session. The predicted outcome from the CBR process was compared to the outcome (A,B or C) predicted by the human expert. These predictions are as follows:

- A: The process completed but with problems (Typically with delays, stalling at some point and/or considerable confusion or disagreement between actors)
- B: The process completed with few or no problems.
- C: The process stalled and had not completed correctly at the point of observation

The results of the investigation can be seen in Table 1 below.

Prediction	MCS <i>(3NN, unfiltered)</i>		Enhanced MCS <i>(3NN, unfiltered)</i>		MCS <i>(3NN, filtered)</i>		Enhanced MCS <i>(3NN, filtered)</i>	
Correct A	12	40.0%	8	26.7%	6	20%	8	26.7%
Correct B	43	78.2%	40	72.7%	43	78.2%	41	74.5%
Missed A	18	60.0%	22	73.7%	24	80%	22	73.7%
Missed B	12	21.8%	15	27.3%	12	21.8%	14	25.5%
Correct C	31	100%	31	100%	30	96.8 %	30	96.8%

Table 1. Comparison of results for the enhanced MCS similarity measures

The results show that the enhanced measures do not provide greater predictive accuracy to the exam moderation business process. Closer investigation of the experiments has shown that in fact in most cases the connected MCS was the important reason and indicator of a problem in the operation of a business process. Providing the enhanced measure had the effect of over-fitting by picking secondary patterns that although common between many business process operations, these were not good predictors of problematic behaviour in the operation of the business process. Although in some cases, this measure can provide further discrimination between the K nearest neighbour cases, the extra computational overhead required to calculate this measure does not justify sufficiently its use in this application. More work is needed to establish whether this can be generalised to more business process application domains or whether this is a feature of the application domain and data used in this experiment.

For the purposes of this evaluation, the enhanced MCS similarity measuring algorithm was applied on a 116X115 cases matrix to calculate all enhanced MCS similarity measures between cases in the case base. Its overall time until completion was 1hr 57sec running on an Intel Core 2 Duo Pentium 2.16 GHz whereas the simple MCS took 11.8 seconds when running with the same dataset and on the same machine. This supports the argument that the computational overhead involved is not justified, at least in the business process application domain considered in this study.

5 Providing context and explanation in CBR-WIMS

Previous work using CBR-WIMS has shown that in order to use effectively CBR to intelligently monitor business processes there is a need to provide context and explanation on the retrieved solutions and advice. This

previous work [5] concentrated on a visual representation of the similarity measures to the business process manager. In particular, the visualisation of the MCS in CBR-WIMS and the ability to drill down into individual historical business operation has been shown to increase trust in the retrieved solutions and thus making the CBR process more effective.

However, all work done so far concentrated on providing some visual explanation on the similarity between cases, not providing any insight or context in the retrieved cases themselves. The system expected the end user to extract any context from the raw retrieved cases.

However, observing business process managers we noticed that once a business process was tagged correctly as problematic, experienced managers could identify certain types of patterns that indicated the existence of certain types of problems. In order to identify such problems we decided to apply cluster analysis to the data available from the exams moderation system.

Due to the structural temporal complexity of cases and the availability of algorithms providing the similarity between cases, rather than possessing a static set of values for each case, it was thought that a hierarchical cluster analysis algorithm could be deployed to attempt to identify particular types of problematic behaviours in the operation of the business processes. A standard Agglomerative Hierarchical Clustering algorithm was applied to the exam moderation data.

The Agglomerative Hierarchical Clustering (AHC) was chosen among others for its unique hierarchy characteristic which organises the clusters in a progressive way based on their similarity distance. In this way individual cases are represented as clusters and clusters that have the highest similarity between them are sequentially merged into a single cluster. The algorithm continues the merging process till the pre-specified number of clusters is reached or when the clusters start becoming too diverse. This can be established by restricting the objective function which represents the mean distance of the cluster members from the notional centroid of a cluster.

The first set of experiments conducted with AHC looked at 5 clusters. As a result of the preliminary AHC experiments we had clusters of a distinctive variety with a combination of cases classified by the expert user as **A**, **B** and **C** as described in part 4 above.

Clusters	As	Bs	Cs	Overall Percentage %
Cluster 1	0	0	11	9.5
Cluster 2	1	0	13	12.1
Cluster 3	12	13	0	21.6
Cluster 4	10	22	7	33.6
Cluster 5	7	20	0	23.3

Table 2. Results with 5 AHC clusters based on MCS

Clusters	As	Bs	Cs	Overall Percentage %
Cluster 1	0	1	0	0.9
Cluster 2	0	0	11	9.5
Cluster 3	1	6	7	12.1
Cluster 4	1	0	13	12.1
Cluster 5	12	13	0	21.6
Cluster 6	4	7	0	9.5
Cluster 7	9	16	0	21.6
Cluster 8	3	12	0	12.9

Table 3. Results with 8 AHC clusters based on MCS

All above experiments have been conducted on a MCSG dataset without any filter application.

An examination of the clusters has shown that only a few of the clusters are clear indicators of the classification of a case as type A, B or C. However, a closer examination has shown that some clusters tend to group together “stories” with similar characteristics. This for example shows some particular feature, such as the intervention of a manager (drafter) who may send an exam paper back to be changed. This may not have necessarily lead to a major problem in the business process operation, but if the business process becomes problematic, it would provide a useful context and explanation for this. In this way the system seems to identify particular event patterns that may cause a problem.

A second set of experiments were conducted based on the components rather than the Maximum common subgraph similarity measures. This ignores largely the duration of temporal intervals between events but concentrates on the existence of events in the business process event trace. In this case, the clusters produced were less able to predict the outcome as A,B,C, but seemed to provide more clear indication interesting patterns of events that may indicate problematic behaviour.

Table 4 shows the results using AHC with the event component similarity only (no MCS). Investigation has shown that in 4 of the clusters there is a clear prevalent event pattern affecting all cases that are members of that cluster. This translates to 35.4% of the whole case base. Some of the other clusters also contain other event patterns, but with smaller degrees of confidence.

To take advantage of this, the explanation component of CBR-WIMS has been enhanced by the inclusion of these event patterns. These patterns have been tagged by a simple text string providing narrative showing the pattern, the possible problems it may cause and advice on possible ways to prevent or remedy the problems.

When the system investigates a new unknown case, CBR-WIMS retrieves the K nearest neighbour cases, together with their known outcome (A, B or C). By a simple voting algorithm the system provides a prediction. Additionally the system allows the user to look at the nearest neighbours, looking at the similarity measures and visualising the Maximum Common Subgraph thus getting some insight into the similarity measures. This can be seen in figure 5. Finally, the inclusion of the text in the cases belonging to the clusters we have managed to tag with specific event patterns provides more context and insight into possible problems in the case study.

The explanation component in CBR-WIMS has shown that it increases the understanding and confidence in the advice provided in the system [5]. The additional inclusion of the event pattern descriptions has shown that it further enhances the usability and effectiveness of the system.

Clusters	As	Bs	Cs	Overall Percentage %
Cluster 1	0	1	0	0.9
<i>Event Pattern 1</i>	0	0	11	9.5
<i>Event Pattern 2</i>	0	0	11	9.5
Cluster 4	1	1	0	1.7
<i>Event Pattern 3</i>	0	3	0	2.6
Cluster 6	1	3	0	3.4
Cluster 7	0	1	1	1.7
Cluster 8	7	16	2	21.6
<i>Event Pattern4</i>	9	3	4	13.8
Cluster 10	0	1	1	1.7
Cluster 11	5	18	1	20.7
Cluster 12	7	8	0	12.9

Table 4. AHC using 12 clusters using event components similarity measure and event pattern identification

Fig. 4 below shows the CBR-WIMS UI module that allows users to “drill down” into the workflow execution logs and identify particular patterns of workflow operation that are flagged as problematic. The user can compare these to real past cases in the case base. The similarity measures are shown, allowing the user to see why a particular workflow problem diagnosis has been made by the system. By examining the relevant parts of the matched cases and browsing all available contextual information, the user can see more clearly any issues identified. The workflow manager can then take appropriate action enabled from a clearer view of the workflow process that is being monitored. Further information in terms of cluster specific patterns, problems and possible solutions further enhance the explanation capabilities of the system.

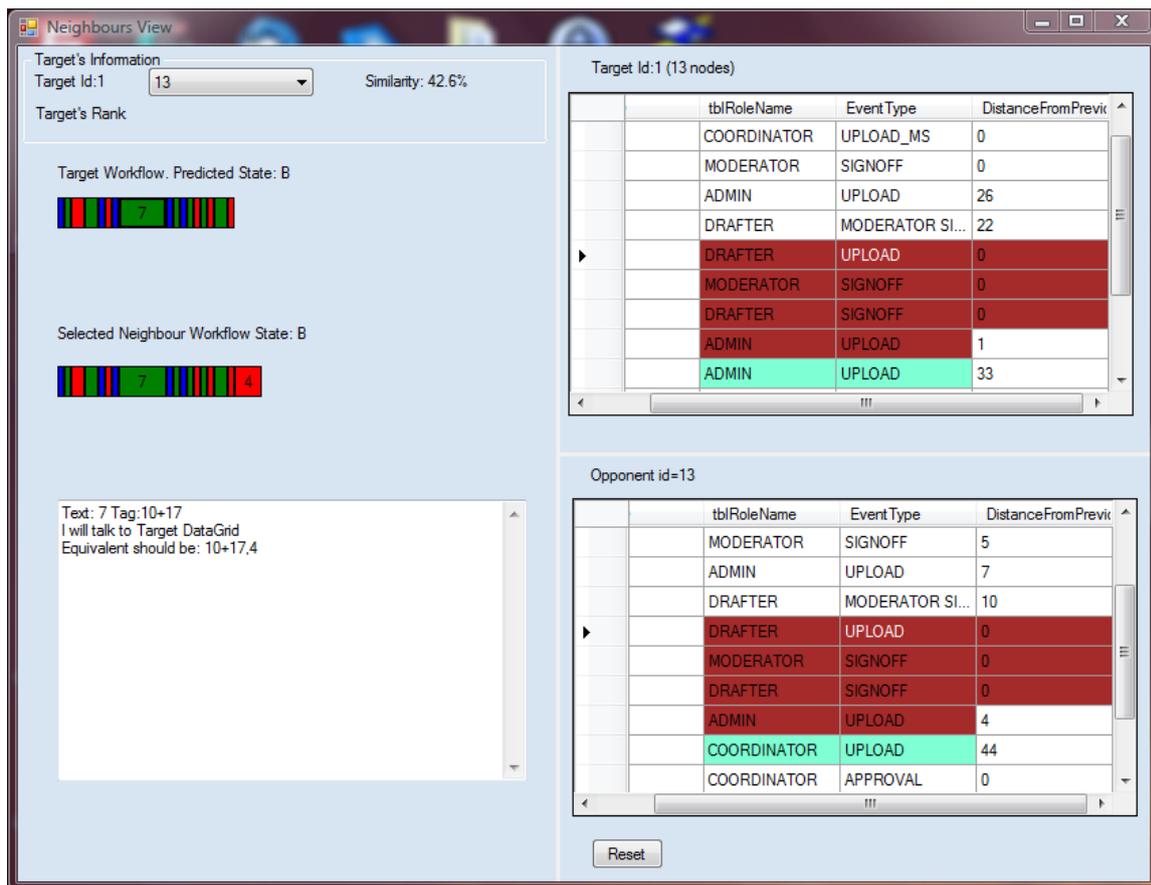


Fig. 4. The Similarity investigation screen in CBR-WIMS

6. Conclusion

This paper discusses recent enhancements to an approach towards the intelligent monitoring of business processes workflows. The CBR-WIMS platform has been developed, which has shown that it can monitor workflows efficiently when compared to human business workflow management experts. Key advantage of proposed system is its ability to adapt and integrate itself into a new and evolving business process in a non-intrusive way. The enhanced similarity measure using multiple, unconnected MCS has shown to be of limited benefit to the application domain used. The use of clustering techniques to identify recurring event patterns and problem “themes” has been shown to provide better insight and a context to business process managers using CBR-WIMS. Future work will concentrate in experiments with data from different business process application areas in order to investigate to what extent current results can be generalised. Further work will also look into the issue of temporal uncertainty combining contextual temporal information to enhance the reasoning process. Finally, further tests are planned to evaluate the ability of CBR-WIMS to adapt to changing business processes with minimum loss of past useful experience and the ability to reason across similar but not identical business processes.

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