A Framework for Case-Based Fuzzy Multicriteria Decision Support for Tropical Cyclone Forecasting

Jocelyn San Pedro & Frada Burstein
School of Information Management & Systems
Monash University, Melbourne Australia
Email: jocelyn.sanpedro@sims.monash.edu.au, frada.burstein@sims.monash.edu.au

Abstract

Case-based reasoning and multicriteria decision making have common grounds: they are both problem solving methodologies; both involve the selection, ranking and aggregation of best alternatives and provide tools for evaluating the alternatives in respect to multiple attributes or criteria. Each of the two methodologies has its own strengths and weaknesses. By integrating the two methodologies, we can take advantage of their strengths and complement each other's weaknesses. This paper proposes a multi-stage framework for intelligent decision support that integrates case-based reasoning and fuzzy multicriteria decision making techniques. We illustrated the proposed approach in the context of tropical cyclone prediction. We describe a prototype intelligent decision support system, which helps the forecaster in retrieving best-fitted solutions in terms of both usefulness and similarity to the current observed case.

1. Introduction

This paper presents a framework for case-based fuzzy multicriteria intelligent decision support that draws upon the integration of case-based reasoning and fuzzy multicriteria decision-making. We identify common tasks involved in both methodologies and explore how the two methodologies may be combined together to build an intelligent decision support model. We are particularly interested in developing a framework that is suitable for real-time decision-making under uncertain and imprecise conditions. We consider tropical cyclone prediction as an illustrative example. The paper begins with brief discussion of common grounds between case-based reasoning and fuzzy multicriteria decision-making, followed by a discussion of the proposed framework. We then describe the forecast process and take a particular stage in the process where intelligent decision support may be useful. This is followed a description of implementation of the proposed framework to tropical cyclone prediction. The paper ends with a discussion of the results and practical implications of application of the framework to tropical cyclone forecasting.

2. Background

Case-based reasoning (CBR) and fuzzy multicriteria decision making (FMDM) have common grounds: they are both problem solving methodologies; both involve the selection, ranking and aggregation of best alternatives; both provide tools for evaluating the alternatives in respect to multiple attributes or criteria; and both provide reasoning to support adaptation of best alternatives.

CBR is a means of solving a new problem by using or adapting solutions to old problems [1]. It solves a problem by retrieving, reusing, revising and retaining past cases that closely match the current problem situation [2]. Past cases are selected based on their degree of match and usefulness to the current situation. This is done by a series partial matching of past cases with the current case, and by ranking across case dimensions until a smaller set of matching and useful cases are retrieved [3]. The degree of match between cases is an aggregate measure of degrees of similarity between corresponding attributes. The usefulness of past cases to the current situation, on the other hand, may be assessed by assigning importance weights. A high degree of similarity or usefulness presents a good reason for adaptation. One of strengths of CBR lies in its capability to use context-based explanation behind solutions to problems [4]. This allows a user to prescribe a solution to the current problem based on the context of the current problem and those of selected past cases. Intelligent technologies however are usually required to utilize context-based explanation of past decisions for real-time decision making. These technologies include the use of fuzzy sets, neural networks, and other soft computing tools that facilitate intelligent retrieval of cases [5,6,7,8]

FMDM solves a decision problem by evaluating and comparing a number of alternatives against several possibly conflicting criteria and selecting the best alternatives despite all sources of uncertainty and imprecision. The decision problem may be classified as either choice problem, sorting problem or ordering problem [9]. In FMDM, best alternatives are selected and ranked according to their degree of preference over other alternatives, instead of degree of partial similarity to just one reference case. The use of preference models in

Proceedings of the 36th Hawaii International Conference on System Sciences (HICSS'03)

FMDM presents a strong assertion that selected alternatives are better than the rest, hence a high degree of preference presents a stronger reason for adaptation compared to degree of similarity to only one reference case. Additionally, the performance of selected alternatives against several criteria also provides an explanation of why and how the best alternatives are selected. Compared to context-based explanation in CBR, simplified criteria assessment presents weaker reasoning because a large amount of details may be lost by quantifying qualitative reasoning.

By integrating the two methodologies, we can take advantage of their strengths and complement each other's weaknesses, but we face the challenge of retrieving best alternatives from a potentially large set of alternatives. Most FMDM techniques cannot handle very large set of alternatives and criteria because they require subjective evaluation of alternatives by the decision maker. In case-based reasoning, an application of preference models yields alternatives that are most similar and most useful to the reference case, and provides means for quick evaluation of decision situation through multiple criteria assessment, but requires additional computations when comparing several alternatives against each other.

In the next section, we propose a framework for intelligent decision support that draws upon the integration of CBR and FMDM. The proposed framework builds upon the common objective of prescribing the best solution and providing reasoning behind such prescription. We address the difficulty of retrieving cases from a large set by dividing the tasks involved in several stages.

3. The Proposed Framework

In this section, we propose a multi-stage framework for combining CBR and FMDM with the aim of building a model for intelligent decision support. The proposed framework is depicted in Figure 1 and described below.

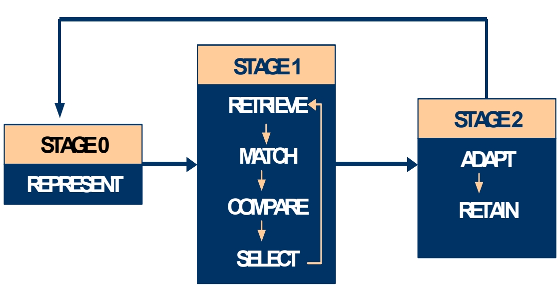

Figure 1. A multi-stage framework for case-based fuzzy multicriteria decision analysis

The proposed multi-stage framework is an extension of a two-stage task-based framework for CBR [10] that uses FMDM technique to solve the case selection problem in CBR. It consists of three stages, namely:

Stage 0. Case representation

REPRESENT current and past cases using multiple attributes and multiple criteria and identify the order by which the attributes and criteria are considered in Stage 1.

Stage 1. Case selection

Perform the following steps sequentially according to the order of importance of multiple attributes:

- RETRIEVE multiattribute information on past cases
- MATCH current and past cases using fuzzy numbers "slightly similar", "similar", "very similar"
- COMPARE past cases with each other using the Pareto domination principle
- SELECT past cases whose degree of dominance are more or equal to threshold value α_i, where $0 \leq \alpha_i \leq 1$ is a threshold value at the i^{th} sub-stage

Repeat the steps sequentially according to the order of importance of multiple criteria, and matching cases using fuzzy numbers "slightly useful", "useful", "very useful".

Stage 2: Case adaptation and retention

ADAPT solution associated with past case or aggregate the solutions of selected past cases and RETAIN information on current case and its solution in a system knowledge base.

Stage 0 is an initialization stage and is concerned with case representation and identification of multiple attributes and multiple criteria and their order of importance. The multiattribute and multicriteria representation of cases allows cases to be described by a full list of attributes where possible and partially described in some aspects where information is not available. Compared to traditional CBR, multiattribute and multicriteria representation of cases avoids the difficulties in retrieval by indexing. It also allows considering partial historical information. Further, Stage 0 also allows faster retrieval of cases in Stage 1. This is because only the necessary information about the cases is retrieved at a particular stage, while the remaining subset of information remains stored in system's memory.

Stage 1 is concerned with the selection of past cases that are "most similar" and "most useful" to a current case according to multiple attributes. Each past case is assessed for similarity to the current case according to multiple attributes. The degree of similarity of a case to the current case is defined as a fuzzy number "slightly similar", "similar" or very similar" defined according to forecaster's judgment. When multiple attributes are considered with varying degrees of importance, we sub-divide Stage 1 into sub-stages so that similarity assessments are performed sequentially according to order of importance of attributes. The selected cases are then assessed for usefulness to the current case. The degree of usefulness of each pre-selected case is defined in linguistic terms "slightly useful", "useful" or "very useful". These linguistic terms may be converted to fuzzy numbers by adapting some scale, for example those suggested in [11]. Scales are determined according to forecaster's judgment.

The search for "most similar" and "most useful" cases follows the Pareto domination principle that selects only those cases that are "superior" to or that "dominate" other cases in the case base. Outranking relations such as Integral Superiority Degree (ISD) [12,13] and those developed by well-known multicriteria methods like ELECTRE [14] and PROMETHEE [15] may be used to measure the degree of superiority or dominance of a case over another. In this paper, we use ISD for our selection schemes. The ISD of x_i over x_j, denoted as ISD(x_i, x_j) is defined by the formula

$$ISD(x_i, x_j) = \sum_{\forall x_k \in X} [SD(x_i, x_k) + SD(x_k, x_j)]/N \quad (1)$$

where

$$SD(x_i, x_j) = \sum_{k=1}^{M} f_k(x_i, x_j) / \sum_{k=1}^{M} \left| f_k(x_i, x_j) \right| \quad (2)$$

$$f_k(x_i, x_j) = \begin{cases} 1, & \mu_T^k(x_i) > \mu_T^k(x_j) \\ 0, & \mu_T^k(x_i) = \mu_T^k(x_j) \\ -1, & \mu_T^k(x_i) < \mu_T^k(x_j) \end{cases} \quad (3)$$

and X is the set of selected cases, M is the number of attributes (or criteria) , N is the number of cases, G_{ik} is a value of the k^{th} attribute (or criterion) for case x_i and $\mu(G_{ik})$ denotes the fuzzy number corresponding to the degree of similarity (or usefulness) of case x_i to the current case according to k^{th} attribute (or criterion). A more general formulation for f is given by

$$f_k(x_i, x_j) = \omega^k [\mu(G_{ik}) - \mu(G_{jk})] \quad (4)$$

where ω^k, when known, is the weight associated to k^{th} attribute (or criterion).

The calculation of ISD requires comparison of fuzzy numbers, as indicated in equation (3) or difference of two fuzzy numbers as indicated in equation (4). Several methods for comparing or subtracting fuzzy numbers appear in literature [16,17] and any method may be applied. Most of these methods require complex procedures and may not be convenient to apply for a large collection of cases. In this paper, we use the fuzzy scoring method [11] that converts a fuzzy number to a crisp score. Using this fuzzy scoring method, we convert $\mu(G_{ik})$ to a crisp score $\mu_T(G_{ik})$ using the following formulas:

$$\mu_T(G_{ik}) = [\mu_R(G_{ik}) + 1 - \mu_L(G_{ik})]/2 \quad (5)$$

where

$$\mu_R(G_{ik}) = \sup_t [\mu_{G_{ik}}(t) \wedge \mu_{\max}(t)] \quad (6)$$

$$\mu_L(G_{ik})] = \sup_t [\mu_{G_{ik}}(t) \wedge \mu_{\min}(t)] \quad (7)$$

$$\mu_{\max}(t) = \begin{cases} t, & 0 \le t \le 1 \\ 0, & otherwise \end{cases} \quad (8)$$

$$\mu_{\min}(t) = \begin{cases} 1-t, & 0 \le t \le 1 \\ 0, & otherwise \end{cases} \quad (9)$$

and $\mu_{G_{ik}}(t)$ is fuzzy membership function derived from $\mu(G_{ik})$ by conversion of range from $G_{ik} \in [a,b]$ to $t \in [0,1]$. $\mu_T(G_{ik})$ then replaces $\mu_T(G_{ik})$ in equation (3) or equation (4).

ISD(x_i, x_j) measures the degree of superiority or dominance of x_i over x_j in respect to all multiple attributes (or criteria) and all other cases. The higher the ISD(x_i, x_j), the stronger is the assertion that x_i is more similar (or useful) to the current case than x_j. ISD is transitive and induces a total pre-order according to decreasing ISD. Superior cases with sufficiently high ISDs may be chosen by prescribing a threshold value. This is one way of controlling the volume of selected cases. We refer to this control scheme as the ISD-rule. A selected case x_i may be assigned a weight w_i defined by first calculating

$$w_i = \max_{x_j \in X} ISD(x_i, x_j) \quad (10)$$

then normalizing so that the sum of weights is a unit.

In Stage 2, an aggregate of solutions of the superior historical cases may be adapted as a solution to the current problem situation. A multicriteria representation of the current case may also be derived as an aggregate of criteria assessments of superior cases. Information on current case and its solution may then be stored or retained in the case base for future use.

The proposed framework selects an aggregate of solutions of "best cases" according to the Pareto domination principle. This final set of similar cases will be derived after taking into consideration additional information about the preferences of the decision maker and also relative importance of the attributes to the current case. This pre-processing procedure justifies the assertion that cases selected in this way are better than the rest of the cases, hence our selection scheme may be regarded more accurate and efficient than traditional selection schemes in CBR. The fuzzy numbers "slightly similar", "similar", "very similar", "slightly useful", "useful" and "very useful" are selected on the assumption that all cases are similar and useful to the current case to some degree according to at least one of the multiple attributes or multiple criteria. By using fuzzy membership functions for assessing similarity and usefulness, we impose a fuzzy categorization of cases, thereby allowing flexibility in the selection of number of cases by varying the threshold value. With such flexibility, it is guaranteed that "not too few" or "not too many" cases are retrieved for adaptation. By converting the fuzzy numbers into crisp scores, we are not losing any of the quantitative properties of the cases, but instead induce a total pre-order of the fuzzy categories. Stage 1 also prescribes a total pre-order of the selected cases if the degrees of superiority are taken as weights of respective superior cases. Such assignment of weights may reduce the uncertainty in weighting cases when aggregating the solutions of past cases, and may potentially improve the level of confidence in the selected solution to the current problem.

Additionally, the integration of FMDM in CBR allows a user to convey his/her preferences in linguistic terms. Thus, the proposed framework provides intelligent assistance to a decision maker by eliciting his/her preferences in terms of similarity and usefulness of available alternatives to the current problem at hand, thereby allowing him/her to learn about his preferences. Criteria assessment of the current situation would provide a quick evaluation of context-based explanation of why and how decisions were undertaken. Thus, a CBR system that provides context-based explanation behind decisions as well as assessment of their usefulness to the current situation makes a powerful tool for supporting real-time decision making based on experiential knowledge. Such CBR system suggests a means for capturing the user's expertise, for imparting expert's knowledge and learning from experience, and thus may be regarded as intelligent decision support system [13,18].

4. Application to Tropical Cyclone Forecasting

Tropical cyclone (TC) forecasting is a very complex task. It involves the estimation of future location, motion and intensity of a current tropical cyclone. There is often considerable scientific uncertainty in dealing with incomplete and possibly conflicting data coming from various sources, wide range of prediction techniques, tight deadlines and high demand for up-to-date and reliable weather prediction. A TC forecaster faces difficult tasks of assimilating all the available data, of choosing the most appropriate combination of techniques, of applying all known conceptual models and operational strategies to come up with reliable optimal forecast products for real-time delivery. These tasks are depicted in the shaded boxes of Figure 2 and described in detail in [19]. The full arrows indicate the traditional sequence of tasks involved in completing the forecast process.

The forecast process begins with the collection of current data that describe the current state of the atmosphere. This large volume of data must be assimilated a number of times each day via parallel manual and computer processing resulting in weather analyses and prognoses. The manual analysis and prognosis requires high level of experience and knowledge of conceptual models of the atmosphere. Computer analysis and prognosis are based on use of mathematical models of the atmosphere running on a supercomputer to simulate the behavior of the real atmosphere. A synthesis of the manual and computer analyses and prognoses forms a reality check on the computer simulations and helps the forecaster choose between the alternatives presented by computer simulation and manual techniques. The forecast products emerge out of this process and must be distributed in real-time.

There is undoubtedly great amount of uncertainty and imprecision by which the forecast products are produced and delivered. The uncertainty and imprecision derives from the amount and quality of subjective judgments from forecasters and level of accuracy of mathematical models representing the true state of the atmosphere, which are inherently subject to errors. The forecast process as described above presents a potential for better decision support. The proposed framework potentially can provide intelligent assistance to the forecaster in coping with the difficult tasks involved in the forecast process. We include the proposed framework for case-based decision analysis among the tasks following the collection of current data as depicted in Figure 2. The case-based fuzzy multicriteria decision analysis links with the manual and computer paths. This link potentially assists a forecaster in assessing the usefulness of historical data to current situation in terms of tasks and several aspects in manual and computer analyses and prognoses. The double arrows indicate sequential application of fuzzy multicriteria decision-making techniques until the forecaster is ready for the synthesis part. The application of the proposed framework will provide reasoning for the synthesis part.

There is a need for post-analysis to validate the official forecasts using the most current observations and verification techniques. Post-analysis results to validated data, which are then stored for use in numerical and objective techniques relying on climatology, and our proposed case-based approach.

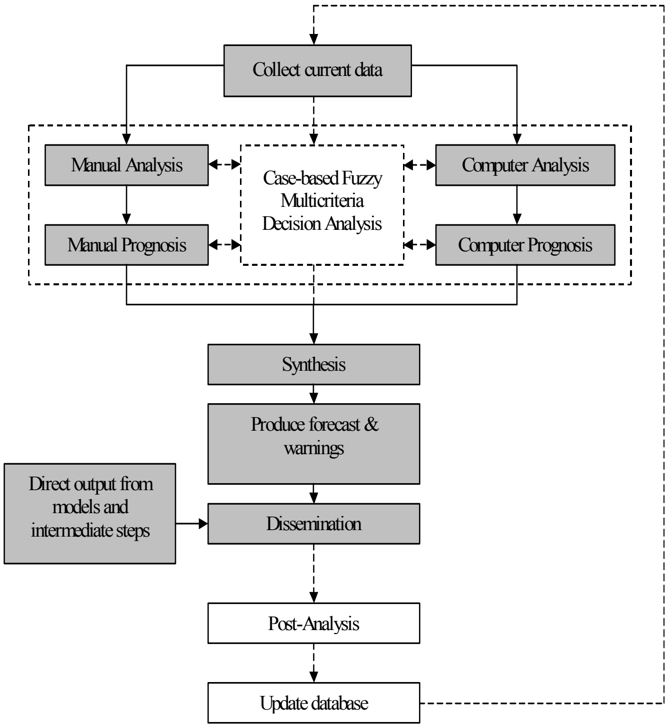

Figure 2. The forecast process incorporating Case-based Fuzzy Multicriteria Decision Analysis

To illustrate how the proposed framework may be applied to TC forecasting, we consider a particular stage of Hurricane Alberto (http://www.nhc.noaa.gov/2000alberto.html) as a current TC case. Alberto is a long-lived Cape Verde hurricane that remained at sea through its lifetime. It is the longest-lived Atlantic tropical cyclone to form in August 2000, and the third-longest-lived of record in the Atlantic. Alberto's track included intensifying into a hurricane three times, a large anticyclonic loop that took five days, and extratropical transition near 53°N).

Table 1 presents 6-hourly observations about Alberto from 08/06/2000/0000 to 08/06/2000/1800 (mm/dd/yyyy/hhhh). We consider track positions (Latitude - oN, Longitude - oW), minimum central pressure (MCP) and maximum sustained winds (MSW) as attributes. Given the past 24 hour observations of a current TC, we wish to predict the track positions and minimum central pressure of the current tropical cyclone for the next 3 days by selecting the best analogs from the case base of past tropical cyclones from 1998 to 2000 in the same region. We consider as "best analogs" those past tropical cyclones whose past 24-hour observations match those of the current cyclone, the 3-day track forecast is the aggregarate of tracks of best analogs, and 3-day intensity forecast is the aggregate of intensities of best analogs.

Table 1. Past 24-hour attributes of TC Alberto

Past 24h TC Attributes	-18h	-12h	-6h	0h
Latitude (^{0}N)	14.5	14.6	14.7	15.2
Longitude(^{0}W)	33.2	34.4	35.4	35.4
CP (hPa)	987	985	983	983
MSW(kt)	65	65	70	75

Using the proposed task-based framework, we proceed as follows:

In Stage 0, we represent the cases in terms of multiple attributes, multiple criteria and the order of importance. For similarity assessment, we consider track positions as first most important attributes and track positions, MCP and MSW as second most important set of attributes. The criteria for evaluating the usefulness of the past cyclones are synoptic history, meteorological statistics, forecast critique and satellite image.

In Stage 1, we select a subset past tropical cyclones depicting similar past 24-hour track positions. The ISDs of these selected past cases are calculated in terms of their fuzzy similarity to the current case. Fuzzy numbers "slightly similar", "similar" and "very similar" are defined in terms of great circle distance between the track positions of past cases and track position of the current tropical cyclone. First application of ISD-rule results to a selection of past cyclones that hit locations close to the current track positions. A second application of the ISD-rule is applied using track positions, MSW and MCP as multiple attributes to select past cyclones that hit the locations with "similar" track positions, MCP and MCP. Fuzzy similarity functions for MCP are defined in terms of absolute difference between MCP of past cases and current case, and fuzzy similarity functions for MCP are defined in terms of absolute difference between MSW of past cases and current case. A third application of ISD-rule filters the selected past cases according to their usefulness to the current situation. For example, a past tropical cyclone with slightly different structure as the current tropical cyclone may be regarded as either "slightly useful" or "useful" or "very useful" to the current situation. A past tropical cyclone that had been predicted with large errors may be "very useful" to the current situation, potentially indicating the difficulty of predicting the future location and intensity of the current cyclone. The ISDs of the selected cases are calculated in terms of their fuzzy usefulness to the current situation resulting to a selection of "most similar" and "most useful" cases.

In Stage 2, these superior cases are then weighted accordingly, and a weighted mean of attributes of the corresponding superior cases determine the position and intensity forecasts for all lead times.

Figure 3 shows a prototype model that implements the proposed framework. The current form displays track chart and attributes (e.g., track positions, great circle distances, names, dates and weights) of top ten cases of past tropical cyclones that are most similar to Alberto. These ten cases correspond to four TCs Gert, Isaac, Cindy and Jeanne. In column S of the table in Figure 3, a forecaster may choose to eliminate some of the past TCs, which for some reason should not be included in the set of analogs. For example, by viewing the chart, a forecaster may choose to eliminate those cases, which for some reason should not be included in the set of alternatives. For example, those past track positions that deviate largely from position of the current TC may be eliminated from the set of alternatives. The TC names and year may assist the forecaster in remembering other information associated with past cases. The weight of a case also may assist the forecaster in filtering the set because the weight reflects the degree by which a case dominates the remaining nineteen cases.

By allowing the forecaster to view details of each selected past TC through Internet link, he/she is able to access past decisions and able to assess whether or not the past case needs to be included in the subset of best analogs. On the right-hand side of the screen shot in Figure 3 is a panel to allow forecaster to subjectively evaluate the usefulness of the past cases according to image, synoptic history, meteorological statistics and forecast critique. The synoptic history describes the structure of the cyclone, which prediction techniques performed well, which rule-of-thumb was implemented, which resources were significant in the forecast product formulation, etc. The forecast critique describes the performance of numerical and objective techniques in predicting the true nature of the cyclone, and the meteorological statistics reports on the level of accuracy of the prediction techniques.

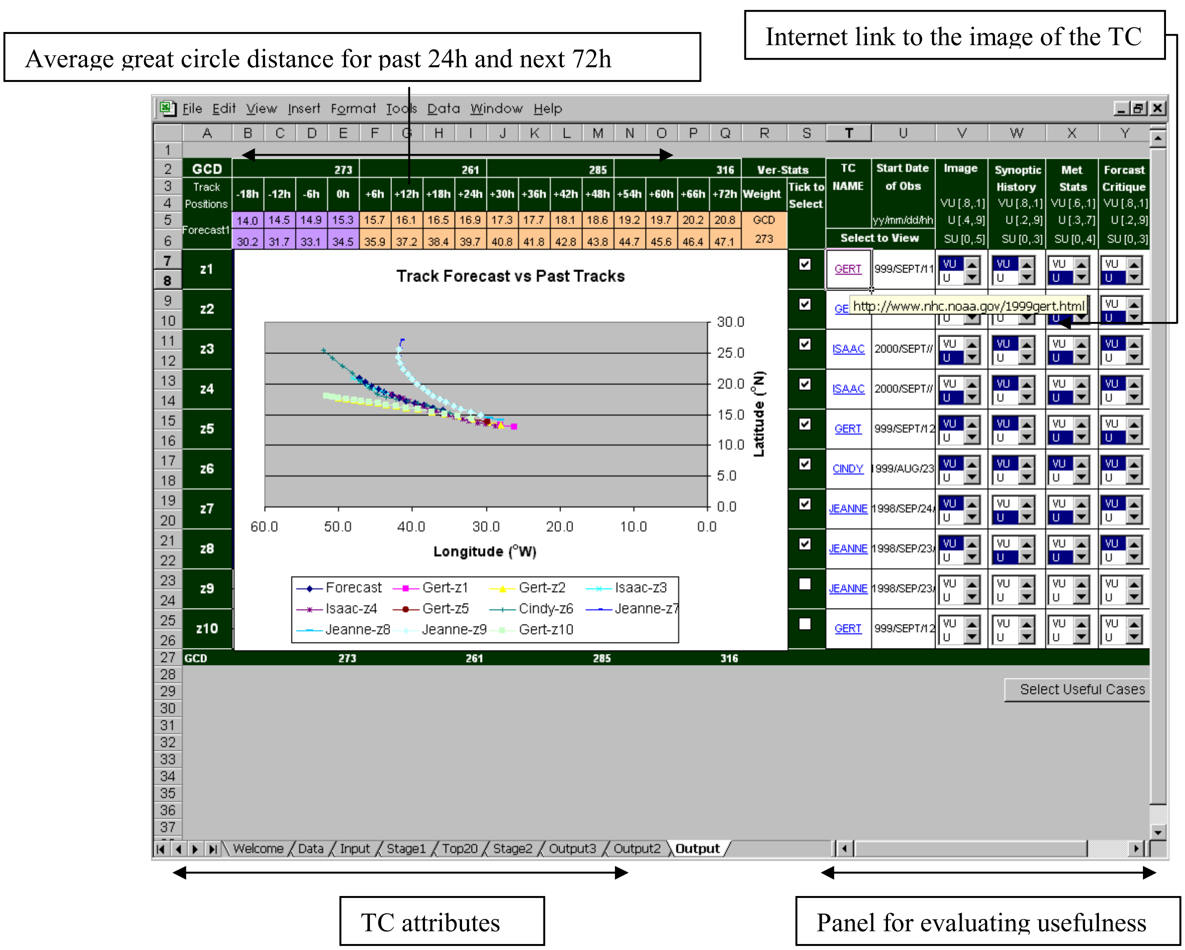

Figure 3. Prototype model for case-based FMDM system for TC prediction decision support

Because other TC attributes were not considered in this paper and only a small subset of historical data were used in our example, no general conclusions can be made regarding the accuracy of the track forecast as compared to results of other forecasting models. It is however recommended that the proposed forecasting technique be considered for comparison to other forecasting models when all important attributes and criteria have been considered.

5. Results and Implications

In the context of tropical cyclone prediction, we can state two potential advantages of the proposed framework. First, the proposed approach may assist forecasters in analyzing large volume to historical data and secondly, it may provide forecasters with intelligent decision support during the difficult tasks involved in the forecasting process.

The multi-stage approach helps in reducing the volume of data from a large set to a smaller subset of most similar cases, then further to a much smaller subset of most useful cases. The final subset is the set of best analogs from which forecasts will be derived. By reducing the amount of information to a manageable size, the proposed approach allows a forecaster to quickly evaluate the filtered set for real-time decision making.

Of great importance to forecasting is the assignment of confidence levels to convey the level of uncertainty and accuracy of the forecasts. The use of outranking relation, such as ISD, potentially may increase the level of confidence in the forecast products. This is because best analogs selected according to ISD are derived with a strong assertion as (a) it draws upon the Pareto domination principle: the best analogs are superior to the others after considering all possible attributes and criteria despite all sources of imprecision, uncertainty and inaccuracy of estimation procedures, and (b) it prescribes a total pre-ordering of the best analogs: the best analogs are weighted according to their degree of superiority.

Current results of this study do not allow any conclusions to be reported regarding improvements achieved in forecasts resulting from the proposed weighting scheme. This is because of unavailability of comparative results of other forecasting models that use different weighting schemes for the same set of historical data and sample current TC used in this paper. We suggest that future research on the proposed forecasting technique should include comparison with other forecasting models.

The proposed approach may further provide intelligent decision support to TC forecaster throughout the forecast process by enhancing knowledge acquisition, reuse and creation. The use of fuzzy MDM in CBR allows a forecaster to convey his/her preferences in linguistic terms. A forecaster's subjective judgments regarding the similarity and usefulness of past cases to a current case will provide explanation as to what, why, when and how particular cases have be selected as best analogs. The use of outranking relations in selecting the best analogs suggests a means for capturing experts knowledge.

Past decisions, actions or consequences associated with the best analogs may also be reused or adapted to justify decisions or actions for the current case. The proposed approach therefore enhances learning from experience. For example, when a current tropical cyclone behaves similarly to past tropical cyclones that caused severe damages to a region, knowledge of the impact of those past cyclones (such as cost of damage, death toll or number of injured people) can be very significant in establishing warning strategies and safety precautions for the current situation.

A new knowledge may be created when a new situation occurs for which there are no relevant past cases. In such case, the proposed approach provides guidance in articulating the forecaster's preferences as to what extent are resources (such as real-time observations and results of numerical weather prediction models) used in the formulation of forecasts and which knowledge components (rules-of-thumb, conceptual models of the atmosphere, traits of numerical models, warning strategies, safety precautions, etc.) may be used to support decisions for the current situation.

6. Conclusions

In this paper, we proposed a multi-stage framework for embedding FMDM technique within CBR to address these concerns. The multi-stage framework consists of an initial Stage 0 to REPRESENT cases in terms of multiple attributes, multiple criteria and identification of the order of significance of the attributes and criteria; Stage 1 that will sequentially RETRIEVE, MATCH, COMPARE and SELECT cases according to multiple attributes or multiple criteria in order of their significance and a final Stage 2 to ADAPT an aggregate of best solutions and RETAIN problem and its solution for future use.

The use of FMDM in CBR potentially leads to more accurate, flexible and efficient retrieval of alternatives that are most similar and most useful to the current decision situation. Additionally, the framework provides intelligent assistance in articulating domain experts preferences through outranking relations.

We illustrated the proposed approach in the context of tropical cyclone prediction. Tropical cyclone prediction is a very complex process requiring analysis of enormous amount of meteorological data, use of several prediction techniques and high level of meteorological expertise. A TC forecaster faces a difficult tasks of assimilating all the available data, of choosing the most appropriate combination of techniques, and applying conceptual models and rules-of-thumb. This paper realizes the need to support the forecasters through these difficult tasks.

The proposed framework potentially may assist a forecaster in analyzing huge volume of historical meteorological data by first reducing the amount of information from a large set to a smaller subset of past cases most similar to the current situation. The amount of information presented to a forecaster at a second stage is further reduced to a smaller subset of most useful cases. By reducing the amount of information to a manageable size, the proposed approach allows a forecaster to quickly evaluate the filtered set for real-time decision-making.

The proposed approach may further provide intelligent decision support to TC forecaster throughout the forecast process by enhancing knowledge acquisition, reuse and creation. By providing a model of forecaster's preferences in terms of similarity and usefulness of past cases to current situation, the proposed framework provides a means conveying the uncertainty and accuracy of decisions with high level of confidence, for capturing experts knowledge, for enhancing learning from past experience and for imparting such knowledge for future decision making.

7. REFERENCES

[1] Riesbeck, C. K. and Schank, R. C.(1989) *Inside Case-Based Reasoning*. Lawrence Erlbaum Associates, New Jersey, USA.

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

[3] Kolodner, J. (1993) *Case-Based Reasoning*, Morgan Kaufmann, California, USA, 1993.

[4] Bartlmae, K. and Riemenschneider, M. (2000) "Case-based reasoning for knowledge management in KDD-projects", *Proceedings of the 3rd International Conference on Practical Aspects of Knowledge Management,* Switzerland.

[5] Yager, R.R. (1997) "Case-based reasoning, fuzzy systems and modelling solutions composition", Case-Based Reasoning Research and Development, Proceedings of the 2nd International Conference on Case-Based Reasoning (ICCBR-97); Leake, D. B. and Plaza, (eds), Springer Verlag, Berlin, 633-642.

[6] Jones, E. and Roydhouse, A. (1995) Intelligent retrieval of archived meteorological data, *IEEE Expert*, 10, 50-57.

[7] Hansen, B. K. and Riordan, D. (2001) Weather prediction using case-based reasoning and fuzzy set theory, in *Proceedings of ICCBR'01: International Conference on Case-Based Reasoning*, Canada.

[8] Pawlak, Z. (1982) "Rough sets", International Journal of Computer and information Sciences 11 (5) 341-356.

[9] Vanderpooten, D. (1990), "The construction of prescriptions in outranking methods", in C. A. Bana e Costa (ed.) *Readings in Multiple Criteria Decision Aid*, Springer-Verlag, Berlin.

[10] San Pedro, J. and Burstein F. (2002) A fuzzy multicriteria decision making approach to case-based reasoning for tropical cyclone prediction, to appear in *Proceedings of DSIAge2002: International conference in Decision Making and Decision Support in the Internet Age*, Dublin.

[11] Chen, S –J. and Hwang, C –L. (1992) Fuzzy multiple attribute decision making: Methods and applications. Springer-Verlag, Berlin.

[12] Zhukovin, V.E., Burstein, F. V.and Korolev, E.S. (1987) "A decision making model with vector fuzzy preference relation", *Fuzzy Sets and Systems,* 22, 71-79.

[13] Burstein, F. and Smith, H. (1995) Case-Based Reasoning for Intelligent Decision Support, *Proceedings of Third International Conference of the International Society of Decision Support Systems ISDSS-95*, Hong Kong, 2, 603-610.

[14] Roy, B., "The outranking approach and the foundations of ELECTRE methods", in C. A. Bana e Costa (ed.) *Readings in Multiple Criteria Decision Aid*, Springer-Verlag, Berlin.

[15] Brans, J.P and Mareschal, B. (1990) "The PROMETHEE methods for MCDM; The PROMALC, GAIA and BANKADVISER software", in C. A. Bana e Costa (ed.) *Readings in Multiple Criteria Decision Aid*, Springer-Verlag, Berlin.

[16] Kaufmann, A. and M. Gupta, (1985) Introduction to Fuzzy Arithmentic. Van Nostrand, New York,

[17] Dubois, D. and Prade, H. (1978) Operations on fuzzy numbers. International Journal of Systems Science 9 (6) 613-626.

[18] Belton, V. And Hodgkin, J. (1999) "Facilitators, decision makers, D.I.Y. users: Is intelligent multicriteria decision support feasible or desirable?", European Journal of Operational research, 113, 247-260.

[19] Linger, H., Burstein, F., Kelly, J., Ryan, C. and Gigliotti, P. (2000) Creating a learning community through knowledge management: the Mandala project, in Carlsson, S., et al. (eds) *Decision Support through Knowledge Management,* Sweden.

ACKNOWLEDGEMENTS

This project is partly funded by the Australian Research Council, Monash University and Bureau of Meteorology.

IEEE COMPUTER SOCIETY