How to Improve Customer Relationship Management in Air Transportation Using Case-Based Reasoning

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Abstract. This paper describes research that aims to provide a new strategy for Customer Relationship Management for Air Transportation. It presents our proposed approach based on Knowledge Management processes, Enterprise Risk Management and Case-Based Reasoning. It aims to mitigate risks facing in air transportation process. The principle of this method consists in treating a new risk by counting on previous former experiments (case of reference). This type of reasoning rests on the following hypothesis: if a past risk and the new one are sufficiently similar, then all that can be explained or applied to the past risks or experiments (case bases) remains valid if one applies it to the new risk or for new situation which represents the new risk or problem to be solved. The idea of this approach consists on predicting adapted solution basing on the existing risks in the case base having the same contexts.

Keywords: Customer Relationship Management, Air Transportation, Knowledge Management, Enterprise Risk Management, Case Based Reasoning.

1 Introduction

The aim of knowledge Management (KM) as an organized and crucial process is to protect the organization's intellectual capital (knowledge of employees) for future benefits. In fact, sharing the right knowledge to the right person, at the right time in the right formats are very important steps that lead to max maximize the productive efficiency of the enterprise. In addition, this knowledge will be used and integrated for business needs in many different contexts (such as production, logistics and transport etc.) in order to increase the organization short and long term value to its stakeholders. In this paper, we study how to improve Customer Relationship Management (CRM) in Air Transportation (AT) using Case Based Reasoning (CBR)? A risk is the probability of the occurrence of an external or internal action which may lead to a threat of damage, injury, liability, loss, or any other negative result, and that may be

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avoided and reduced through preemptive action [1] [2]. For example: death, injuries form turbulence and baggage, dissatisfaction, bad provision of information, bad communication , misunderstanding, noise and mobility, bad cleaner staff, bad service quality, bad presentation of safety rules, lack or lost of baggage, uncomfortability of customer, lack of respect etc. Generally, these risks have great impacts on the achieving the origination objectives. In this context, our approach's aim is to mitigate the danger based on the interaction between Enterprise Risk Management (ERM) and KM and using the CBR. The idea is to deal with all the risks that may affect customer during the air transportation process from the registration of the customer to the analytics and feedback post-journey. Furthermore, it also endeavors also to create new opportunities in order to enhance the capacity of building a perceived value to its customers.

2 The Proposed Approach Overview

Based on KM processes [3], our method has four phases (Fig. 1): (1) Knowledge creation and sharing phase, (2) Knowledge analyzing phase, (3) Knowledge storage phase, (4) Knowledge application and transfer phase.

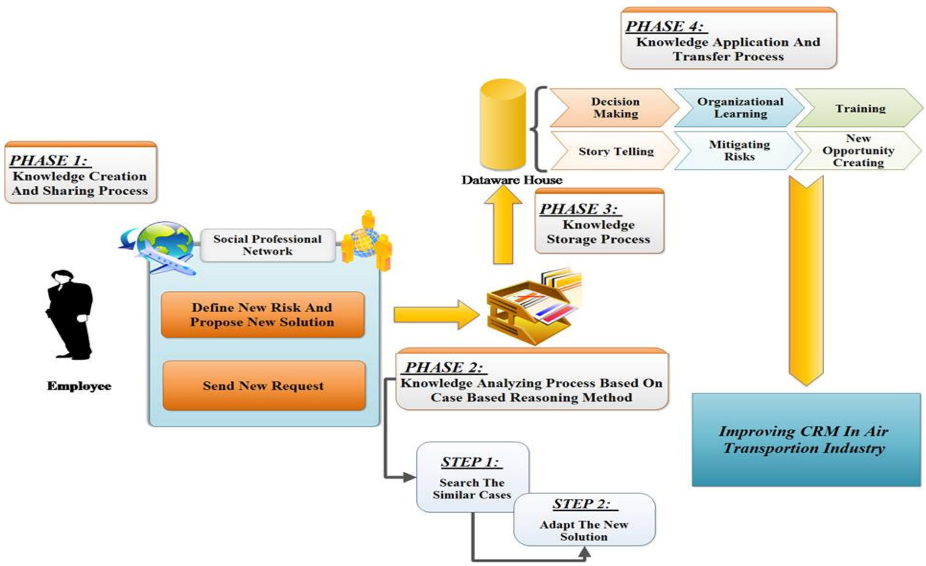

Fig. 1. Our research model design

2.1 Knowledge Creation and Sharing Process

The purpose of this phase is the identification of risk caused customer dissatisfaction. It includes two steps as below:

Identification of Risk and Proposition of Its Appropriate Solution. Each employee adds the risk faced during the air transportation process and that may affect customer satisfaction (such as noise, mobility, bad services, lack of safe, bad communication, lack of baggage, misunderstanding etc). Then he proposes its associate solution in the professional social network in order to, create a Community of Practice (CoP)[1] with other employees, discussing the relative issue and generating a number of solutions (references cases).

Formulate New Request. The employee faces a risk and wants to know how to solve it. He formulates a request to the system specifying the risk. The system treats the request based on the CBR method and answers the employee with the appropriate solution adapted on his/her context based on fuzzy logic.

2.2 Knowledge Analysis Process

The goal of this phase is the optimization of the best adequate solution associated to each risk defined using the CBR. Case-based reasoning is used to solve a new problem by remembering a previous similar situation and by reusing information and knowledge of previous situations. It is based on the following hypothesis: if a past experience and a new situation are sufficiently similar, then everything can be explained or applied to past experience (case base) is still valid when it's applied to the new situation that represents the new problem to solve [5] [6] [7].

The purpose of CBR is to composite a relevant solution in current context by comparing it with other similar contexts of use. CBR is composed by four steps: selecting the similar cases, fuzzy adaptation, revision and learning. The two latest steps (revision and learning) are described in the following phase.

Step1: Selecting the similar cases. This step is based on the contextual filtering. The system uses the characteristics of context in order to compare the new case (NC) with the existing cases (EC) using the following formula:

$$\text{Sim (NC, EC)} = \sum_{a=0}^{A} \frac{NCxa - ECxa}{DM} \quad (1)$$

With NC is the new case, EC is the existing one.

A is the set of the user attributes; NC_{xa} represents the value of the current user attribute and EC_{xa}, the value in the existing contexts.

DM is the difference between the maximum threshold and the minimum threshold.

B_c is the case base filtered by selecting similar cases of the current user request (risk) in the context C.

The contextual filtering aims to measure the similarity between the current context and the existing contexts basing on the Pearson correlation. In this context, the most similar cases are selected from the collection B_c. The context C_i is composed by a finite

[1] Communities of Practice (CoP) are techniques used in KM, the purpose is to connect people with specific objective that voluntarily want to share knowledge [4].

set $\{a_{1i}, a_{2i}, \ldots, a_{ni}\}_{i,n \in \mathbb{N}}$ that differs in number from a risk to another. Two contexts are similar if its attributes are respectively similar. $C_1 = a_{11} \cup a_{21} \cup \ldots \cup a_{n1}$; $C_2 = a_{12} \cup a_{22} \cup \ldots \cup a_{n2}$ with $n \in \mathbb{N}$.

$$\mathrm{Sim}\,(NC; EC) = (\mathrm{Sim}_R\,(R_i; R_j), \mathrm{Sim}_C\,(C_i; Cj)) \tag{2}$$

$$\mathrm{Sim}_C\,(C_i; C_j) = (\mathrm{Sim}\,(a_{1i}; a_{1j}), \mathrm{Sim}\,(a_{2i}; a_{2j}), \ldots, \mathrm{Sim}\,(a_{ni}; a_n))_{i,j,n \in \mathbb{N}} \tag{3}$$

With a_n represents an attribute that characterises the context C.

And i, j are the coefficients of two different contexts relative to the same risk.

$$\mathrm{Sim}(NC; EC) = (\mathrm{Sim}_R(R_i; R_j), \mathrm{Sim}\,(a_{1i}; a_{1j}), \mathrm{Sim}\,(a_{2i}; a_{2j}), \ldots, \mathrm{Sim}(a_{ni}; a_{nj})_{i,j,n \in \mathbb{N}}) \tag{4}$$

Step2: Adapting the new solution. Basing on the selected cases, the idea is to propose an adapted solution to the new context. It is a combination of many parts of the solutions (Si, Sj …) from the most similar cases. To this end, this step is segmented into three levels fuzzification, fuzzy inference and defuzzification.

Fuzzification. It is the process by which an element is rendered diffuse by the combination of real values and membership functions. It converges an input determined to a fuzzy output. The similarities corresponding to the different dimensions of context calculated in the previous phase are the input variables of fuzzy system.

The fuzzy system is based on n attributes of the context as inputs: $\mathrm{Sim}(a_{1i}; a_{1j})$, $\mathrm{Sim}\,(a_{2i}; {}_{a2j})$, …, $\mathrm{Sim}(a_{ni}; a_{nj})$ with $i, j, n \in \mathbb{N}$.The system output is the relevant solution "S" which is the combination of many parts of the solutions (S_i, S_j …) from the most similar cases. These input and output variables are the linguistic variables of the fuzzy system.

The linguistic variable is represented by:

Sim is the similarity of the context attribute between two similar contexts i and j with i, j $\in \mathbb{N}$.

L is the set of linguistic terms.

U is the universe of discourse.

$$\text{Number of rules} = L^n * S \tag{5}$$

With n is the number of fuzzy system inputs.

S is the number of output

Fuzzy inference. It aims to assess the contributions of all active rules. The fuzzy inference is affected from a rules database. Each fuzzy rule expresses a relationship between the input variables (context attributes similarity Sim) and the output variable (relevance of the solution "S"). The fuzzy rule in our approach is as follows:

If (Sim is A) Then (S is B)

Where Sim is the context attributes similarity correlated (the premises of the rule), S is the relevance of the solution (the conclusion of the rule), and A and B are linguistic terms determined by the fuzzy sets.

In the Mamdani model, the implication and aggregation are two fragments of the fuzzy inference. It is based on the use of the minimum operator "min" for implication and the maximum operator "max" for the aggregation rules.

Defuzzification. It is the process by which fuzzy results of similarities correlated are translated into specific numerical results indicating the relevance of the solution. After combining the rules obtained, we must produce an encryption output. The evaluation of the solution is implemented based on "Mamdani" model.

In our inspired Mamdani model approach, defuzzification is performed by the center of gravity method of rules results.

$$F\,(r_i,c_i,s_i) = \frac{\int \mu(s)\, s\, d_s}{\int \mu(s)\, d_s} \tag{6}$$

$F(r_i,c_i,s_i)$ is the function associated with the case c_i with $\mu(s)$ is the membership function of the output variable s_i and r_i is the rules.

The fuzzy inference releases a sorted list of relevant solutions L^F.

$$L^F = \{(s_i, F(r_i,c_i,s_i)) \setminus (r_i,c_i, c_i) \in B_c\}$$

The informational content S^I is an integral part of the relevant solution from the sorted list L^F of relevant solutions, maximizing the similarity Sim correlated to the retrieved case. The solution recommended to the user is a combination of torque solutions (S^I).

2.3 Knowledge Storage Process

To be usable, a base of case must contain a certain number of cases. An empty base of case does not allow any reasoning. Consequently, it is important to initiate the base of case with relevant cases. To this end, the adapted solutions will be revised by the evaluator. Then, the validated solutions will be added to the base of cases $B_C = B_C \cup \{R_p, C_p, S\}$. In fact, Learning involves the enrichment of the context of use and solutions.

2.4 Knowledge Application Process

This phase represents that the transfer and the use of knowledge can enhance customer value. In this level, decision maker interprets these results (e.g., statistics, classification) and suggests a radical way for a new improvement process through training, storytelling, lesson learned etc [7].

3 Application in Air Transportaation

In order to validate our method, we have implemented a professional network in air transportation described in the following figure (cf.Fig.2). This application provides employees with a relevant solutions responding to the current risk basing on the previous experiences. In an integrated development environment “Netbeans”, we developed the application integrating Java API/ Matlab Control.

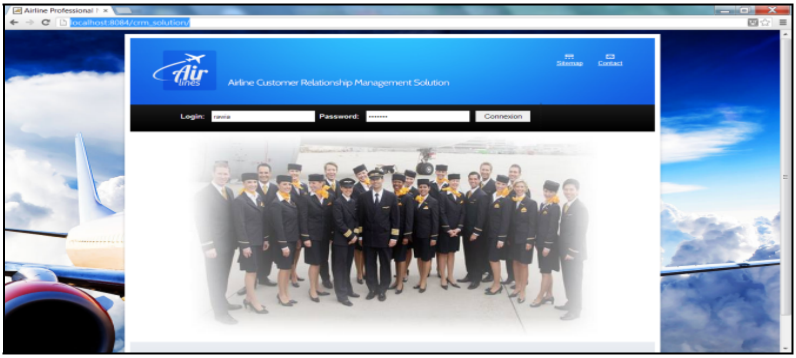

Fig. 2. Professional network for air transport service

3.1 Phase 1: Knowledge Creation and Sharing Process

When an employee is faced a new risk, he can formulate a new request in order to find an appropriate solution. The figure 3 presents the interface that can be used by an employee.

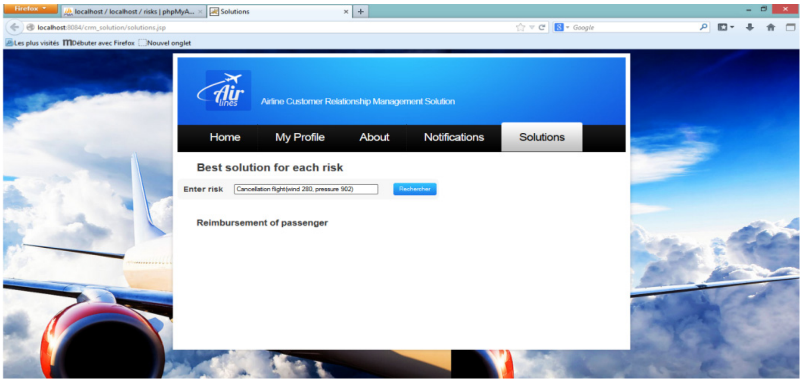

Fig. 2. Example of an employee request

This request must include the current context. The figure 4 presents an example of a context.

Risk: Cancellation flight

Context: Weather condition

C_2= Hurricane Charley (2004) = Wind 150 mph (240 km/h), pressure 941 mbar (hPa); 27.79 inHg

C_1= Hurricane Katrina (2005) = Wind 175 mph (280 km/h), pressure 902 mbar (hPa); 26.64 inHg

Fig. 3. Example of a context

3.2 Phase 2: Knowledge Analyzing Phase

Step1: Selecting of similar cases. We have to calculate the Sim of the context between the new case C_1 and the existing case C_2 as follow:

$$Sim_C(C_1, C_2) = (0.545) \tag{7}$$

Step 2: Adapting the new solution. This step is divided into three levels as below:

Fuzzification. The fuzzifier mapes two inputs numbers (Sim(wind) and Sim(pressure)) into fuzzy membership. The universe of discourse represents by U = [0, 1]. We propose Low, Medium and High as the set of linguistic terms. The membership function implemented for Sim(wind) and Sim(pressure) is trapezoid.

The figure 5 describes the partition of fuzzy classes. It aims to divide the universe of discourse of each linguistic variable on fuzzy classes. It is universal for all the linguistic variables as below: Low [-0.36 -0.04 0.04 0.36], Medium [0.14 0.46 0.54 0.86], High [0.64 0.96 1.04 1.36].

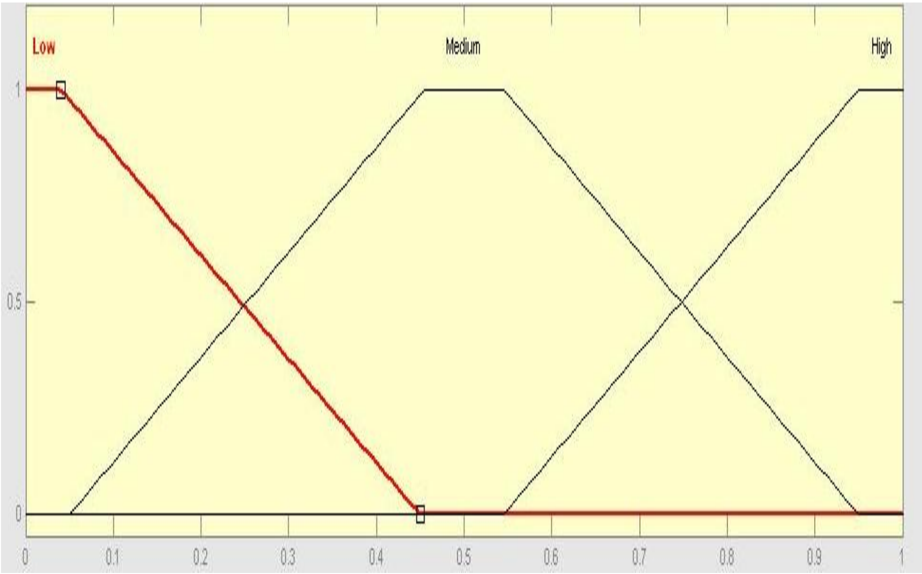

Fig. 5. Partition of fuzzy classes

Fuzzy inference. It defines mapping from input fuzzy sets into output fuzzy sets basing on the active rules (cf. Fig. 6). The number of rules in this case is: $3^2 * 1=9$ rules.

R1: If (Sim(pressure) is Low) and (Sim(wind) is Low) Then S is Low
R2: If (Sim(pressure) is Low) and (Sim(wind) is Medium) Then S is Low
R3: If (Sim(pressure) is Low) and (Sim(wind) is High) Then S is Low
R4: If (Sim(pressure) is Medium) and (Sim(wind) is Low) Then S is Low
R5: If (Sim(pressure) is Medium) and (Sim(wind) is Medium) Then S is Medium
R6: If (Sim(pressure) is Medium) and (Sim(wind) is High) Then S is High
R7: If (Sim(pressure) is High) and (Sim(wind) is Low) Then S is Medium
R8: If (Sim(pressure) is High) and (Sim (wind) is Medium) Then S is Medium
R9: If (Sim(pressure) is High) and (Sim (wind) is High) Then S is High

Fig. 6. List of fuzzy rules

Defuzzification. It is based on Mamdani model (cf. Fig.7) which incorporates the center gravity method by the evaluation of the set of rules in the fuzzy inference. It maps output fuzzy into a crisp values.

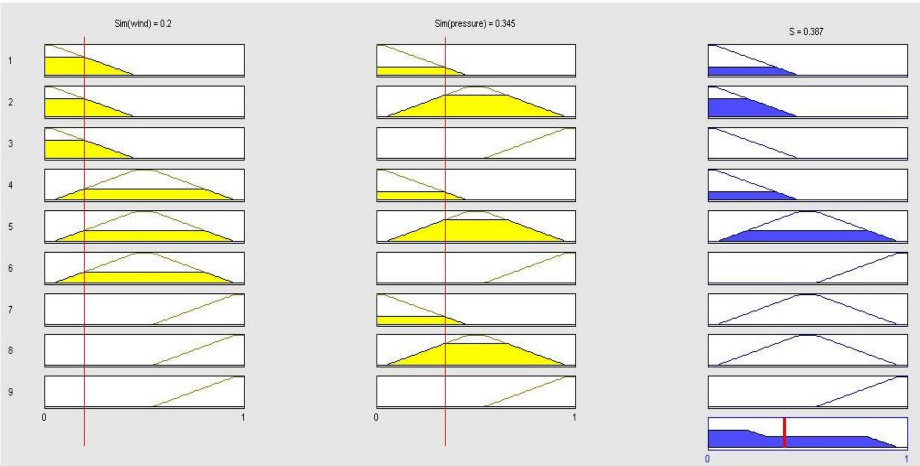

Fig. 4. Mamdani Inference: Activation of the result S

For the example of Hurricane Katrina, the solution is adapted from the solution of Hurricane Charley (wind= 280, pressure= 902) F= 0.387.

3.3 Phase 3: Knowledge Storage Process

At this level of our work, the adapted solution resulted from the previous phase will be evaluated by an expert. Then, the validated solutions will be retain in the case base.

3.4 Phase 4: Knowledge Application Process

Training and lesson learning session will be establishing for the employees basing on the case base retained from the previous phase. The purpose of this process is to exploit the previous experiences in order to improve the intellectual capital and competences of the employees and facilitate the management of risk caused customer dissatisfaction.

4 Conclusion

In this paper, we presented a crucial and generic approach based on the interaction between two disciplines KM and ERM and using CBR and fuzzy logic in order to enhance CRM in AT. First, by identifying risks caused customer dissatisfaction. Second, proposing new solutions responding to risks faced in all touch points of the AT process. Finally, the application of a learning process from the previous experiences (risk and solutions) for the employees will be established. A challenge for future research will be to refine the optimization of the adapted solution based on genetic algorithm.

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