Generalizing GAMETH®: Inference rule procedure

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Abstract. In this paper we present a generalisation of GAMETH framework, that play an important role in identifying crucial knowledge. Thus, we have developed a method based on three phases. In the first phase, we have used GAMETH to identify the set of "reference knowledge". During the second phase, decision rules are inferred, through rough sets theory, from decision assignments provided by the decision maker(s). In the third phase, a multicriteria classification of "potential crucial knowledge" is performed on the basis of the decision rules that have been collectively identified by the decision maker(s).

Keywords: Knowledge Management, Knowledge Capitalizing, Managing knowledge, crucial knowledge.

1 Introduction

Capitalizing on company's knowledge is increasingly being recognized in a private organizations environment since managing knowledge productivity is considered a source of competitive advantage. In the automotive sector, capitalizing on the knowledge used in design process, that is, locating, preserving, enhancing value and maintaining this knowledge is very complex (Saad et al. 2002). It involves more and more heavy investments in order to convert unstructured tacit knowledge into explicit knowledge to be integrated in corporate memory defined as "Explicit, disembodied, persistent representation of knowledge and information in an organization" (Van Heijst et al. 1996). The automotive company PSA Peugeot Citroen, used a different type of tools to preserve knowledge:

- "The Book of Knowledge" Ermine (2003) to preserve knowledge used and produced in design project
- The Knowledge-Based-System (KBS) is used to help human users in achieving tasks in application domains

As resources of the company are limited, the automotive company must define accurately the knowledge to be integrated in the design process's corporate memory.

In our case study, the goal is to propose a method to identify and qualify crucial knowledge in order to justify a situation where knowledge capitalization, specifically in the context of decision-making, is advisable.

The rest of the paper is organized as follows. Section 2 synthesizes the related research studies. Section 3 presents experimentations. Section 4 presents the methodology. In Section 5 we present the application of the methodology in the PSA Peugeot Citroen French Company. Section 6 concludes the paper and presents our current and future work.

2 Research studies

In literature, there are only few works that are interested in the delimitation of the knowledge on which capitalization operation need to be conducted, e.g. [3] [25]. Several authors, including [3] [4] [9] [5] [25] consider crucial knowledge delimitation process as a hard operation.
The need for pertinent and crucial knowledge in any knowledge capitalizing operation has been proved by several authors (e.g. [2] [10] [13] [25]). Only few theoretical and empirical works are available in literature. We may distinguish two classes of methods: methods based on knowledge domains and methods based on processes. The main distinctive feature of these methods is related to the approaches used (i) to collect knowledge to be evaluated and (ii) to construct criteria and evaluate knowledge in respect to these criteria.
Concerning knowledge collection, we think that the method proposed by [10] enables to study the area and to clarify the needs in knowledge required to deal with pertinent problems through the modelling and analysis of sensitive processes in the company. This approach involves all the actors participating in the area of the study. In similar way, [5] bases on identifying the process to identify the sources of information. [25] use the DELPHI method to collect the need in knowledge. The merit of this method is the fact that they are faster to apply than the one of GAMETH. Further, DELPHI technique may be used distantly. The approach of [17] is based on interviews with "manager" in order to identify the needs in knowledge. Finally, the method proposed by [4] is evenly based on both a series of interviews with the leaders and, the study of strategic documents. These two last approaches suppose that the leaders are able to identify the knowledge to evaluate.

Our analysis of these approaches at the level of criteria construction and knowledge evaluation permits us to remark that the methods proposed by [4] [10] [17] construct criteria intuitively. In turn, Tseng and Huang propose to compute the average score of each attribute of the knowledge as a function of the evaluations provided by each analyst. Then, the analyst evaluates the important of each knowledge in respect to each problem. Finally, the average global is computed for each analyst. One limitation of this method is that the scales used are quantitative. However, due to the imprecise nature of the knowledge, qualitative scales are preferred.

3 Experimentation

We carried experiments in order to show whether the decision rules resulting from the identification phase of crucial knowledge (section 3.1) are effective. We considered a set of forty potentially crucial knowledge items and classified them in two classes: (1) "no crucial knowledge" (Cl_1) and (2) "crucial knowledge" (Cl_2).

	DM 1	DM 2	DM 3	DM 4	Average
Cl_1	0,46	0,58	0,30	1	0,58
Cl_2	0,75	0,81	0,77	1	0,83

Table 1: Quality of approximation

The evaluation of each knowledge in this test set is carried with the help of the decision maker. Table1 reports the quality of approximation with respect to four individual decision rules corresponding to four decision makers (DM). The average 0,83 of

Figure 1 shows that we have various results depending on the decision maker's preferences. In addition, the average of approximation quality of crucial knowledge determine with GAMETH framework is 0, 83.

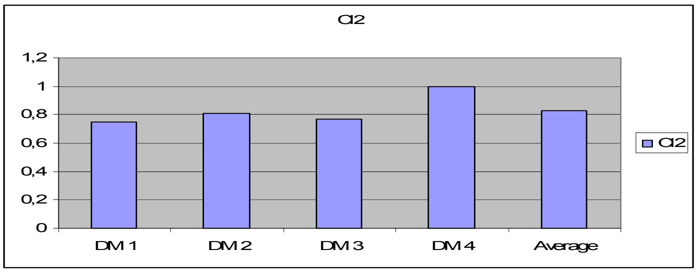

Figure 1. Approximation quality of crucial knowledge

4 Methodology

The methodology for crucial knowledge identification and evaluation is composed of three phases (Figure 2). A detailed description of it is available in (Saad, 2005).

Phase 1: Determining "Reference Knowledge"

The first phase is relative to constructive learning devoted to infer the preference model of the decision makers. Constructive learning, as opposite to descriptive learning, suppose that the preference model is not pre-existing but is interactively constructed by explicitly implying the decision maker. Practically, it consists in inferring, through the DRSA (Dominance-based Rough Set Approach) [6] method which is an extension of rough set theory [15] and which is devoted to multi-criteria sorting problems of a set of decision rules from some holistic information in terms of assignment examples provided by the decision makers. This set of rules may be used in the same project or in other similar or new projects. However, for similar or new projects an adaptation of the set of decision rules to the project under consideration often required. This phase includes also the identification, using GAMETH (Global Analysis METHodology) framework [10], of a set of “knowledge of reference”.

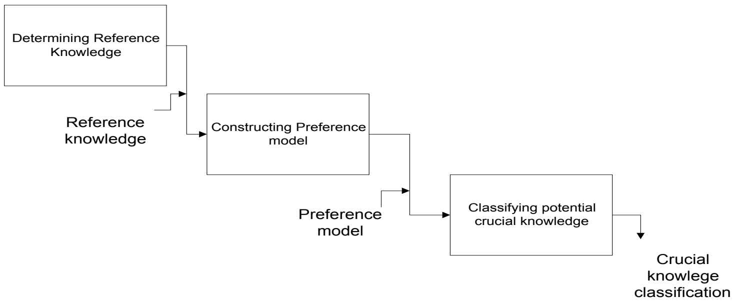

Figure 2. The methodology for crucial knowledge identification and evaluation

Phase 2: Constructing Preference model

The second phase includes the construct of preference model and the evaluation of knowledge with the respect to a convenient set of criteria. The criteria used in our application are summed up in the Appendix 1. Inspiring from the systemic approach of [11] and by using the bottom-up approach, three sub-families of criteria where constructed: (i) knowledge vulnerability family that are devoted to measure the risk of knowledge lost and the cost of its (re)creation; (ii) knowledge role family that are used to measure the contribution of the knowledge in the project objectives. Each criterion of this family corresponds to an objective; and (iii) use duration family that is devoted to measure the use duration of the knowledge basing on the company average and long term objectives. The criteria used to evaluate the “knowledge of reference” were constructed through a combination of the top-down and bottom-up approaches. The top-down approach was used to identify the indicators from which the criteria $g_1,\ldots, g_{15}$ in the Appendix are constructed. These indicators were defined basing on the theoretical research in knowledge engineering, strategic management and artificial intelligence domains and on the empirical studies conducted in the PSA Peugeot Citroen company see [23] for details.

To make the evaluation phase easier, we should analyze the “knowledge of reference”, i.e. identify the process where the knowledge is used, the person gathers it, the tacit level, production time and see if it is validate or not.

To evaluate each knowledge K_i in respect to the each objective O_j, we have developed the computing model [21] [22]. The evaluation of knowledge in respecter to criteria of families (i) and (iii) are normally provided by the decision maker. However, in practice the decision makers may show some difficulty in directly evaluating knowledge in respect to some complex criteria. To overcome this problem, complex criteria are decomposed into several more simple indicators. The decision makers can easily evaluate these indictors.

Once all knowledge items are evaluated with respect to all criteria, the next step is an iterative procedure permitting to conjointly infer the decision rules. Two decision classes have been defined Cl_1: "non crucial knowledge" and Cl_2: "crucial knowledge". This procedure is composed of four substeps.

- The first substep consists in determining, with the help of each decision-maker, assignments of a set of knowledge items "knowledge of reference" in the following decision classes: *Cl1* "non crucial knowledge" and *Cl2* "crucial knowledge".
- The second substep consists in inferring decision rules for each assignment sample determined in the preceding stage. To do so, we use the DRSA (Dominance-based Rough set approach) method [6], which extends the classical rough sets approach proposed by [15].
- The third substep consists in modifying sample assignments or evaluations with the concerned decision-maker, when inconsistencies are detected in the decision rules base.
- The last substep consists in determining decision rules that are collectively accepted.

Phase 3: Classifying potential crucial knowledge

In the third phase, the decision maker use the preference models of the different stakeholders defined in the first phases to assign the new knowledge, called "potential crucial knowledge", to the classes Cl1 or Cl2. More specifically, a multi-criteria classification of "potential crucial knowledge" is performed on the basis of the decision rules that have been collectively identified by the decision maker(s) in the first phase. The term of "potential crucial knowledge" should be mapped to the concept of "potential action" as defined in the multi-criteria decision-aid theory, that is, "real or virtual actions considered by at least one stakeholder as a temporally realistic one" [19]. The term "stakeholder", as defined by [19], refers to "individuals or groups of individuals who, because of their value system, directly or indirectly influence the decisions, either at first degree because of their intervention or at second degree by the manner in which they use the action of other individuals". Thus, "potential crucial knowledge" is the knowledge that has been temporary, identified as crucial by at least one stakeholder. The generated "potential crucial knowledge" are analyzed and then evaluated against the criteria identified in the first phase. Then, they are assigned in one of two decision classes Cl1 or Cl2. This phase composed of four steps. The second and third steps are similar to those of the first phase. In the first step the decision makers identify the set of "potential crucial knowledge" to be evaluated. In practice, it is often difficult to evaluate all the knowledge. Several methods may be used to support the decision maker in this step as DELPHI [25] and GAMETH. We think also that some other methods IBIS (Issue-Based Information System), QOC (Question, Options, Criteria) (see for e.g. [1]) and DRCS (Design Rationale Capture System) (see for e.g. [3]) which are initially devoted to model the evolution of the decision making process may be applied to this problem. In our case study we have used the GAMETH method. A discussion of these different methods and the situation to which they are advised is detailed in [20].

In the last step, the rules base is used to classify new knowledge items which we call "potential crucial knowledge", into one of the decision classes Cl_1 and Cl_2. In fact, one "potential crucial knowledge" is regarded as effectively crucial if there exists at least one decision rule within the rules base, whose premises are paired with the evaluation of this knowledge on the set of criteria. The general form of a decision rule is:

If $g_j(k) \geq r_{gj}\ ;\ \forall j \in \{1,\ldots,m\}$ then $k \in Cl_2$

where

- $g_1, \ldots, g_m$ is a family of m criteria,
- $g_j(k)$ is the performance of the knowledge k on criterion g_j ,
- $(r_{g1}, \ldots, r_{gm}) \in V_{g1}$ x …x V_{gm} is the minimum performance of a knowledge k on the set of criteria.

5. Case study

The proposed methodology was conceived and validated in the PSA Peugeot Citroen French Company. More specifically, we have focalized on the FAP (Particle-based Filter) development projects: FAP_x, FAP_y, FAP_z and FAP_w (x, y, z and w denote the successive generation of FAP system). FAP is a depollution system integrated in the exhaust system. The objective of PSA Peugeot Citroen company is to transfer the knowledge developed in the FAP_x for use:

- with other types of vehicles
- with projects concerned with definition of the new systems of FAP(i.e FAP_y, FAP_z and FAP_w)

5.1 Phase 1: Determining "Reference Knowledge"

To identify the "knowledge of reference", we have applied GAMETH framework. This framework is composed of four steps. The first step is composed of four substeps. The first substep permits to define the organizational model of the FAP project under study, i.e., define the study area, construct the organization chart and formalize the objectives in hierarchical form to help the decision makers identify sensitive processes. For example, the objective "Ameliorate the reliability of the FAP system" may decomposed into three sub-objectives: "Goodness of the choice of the filter support", "Goodness of choice of the additive" and "Adaptability of the strategy". The "Adaptability of the strategy" sub-objective may in turn be decomposed into: "Ameliorate the strategies related to supervisor" and "Ameliorate the strategies related to the help of regeneration". In the second substep we identify, with the help of the project responsible, the sensitive processes. Two sensitive processes are: "Choice of filter support" and "Design and methodology of supervisor calibration". The third substep concerns the modelling and analysis of these processes as well as the study of "critical activities" associated with each process. In the last

step we identify the sources of knowledge and their localization. The result of this last substep is as in Table 3. We have identified in our study case 2 sensitive processes, 4 critical actives and 34 “knowledge of reference”.
The knowledge K_1 is in part gathered by two experts (in activity A) called Y and W (for confidentiality, experts will be denoted with capital letters); and in part formalized in a technical documents accessible on Intranet for concerned users. The manager of this knowledge is the expert X. Finally, K_1 is incomplete.

Table 3. An example for identifying sources of the knowledge

Knowledge	Source	Location	Knowledge manager	Quality
K1: the role of the supervisor of the first generation	Gathered in part by experts Y and W and in part prescribed in technical documents	The two actors and documents are associated with activity A and locate in site G	Manger of K1 authorizes the access	Incomplete

5.2 Phase 2: Constructing Preference model

1) Step1. In-depth analysis of “knowledge of reference”: The second step of our methodology concerns the analysis in depth of knowledge. Since our objective is to identify crucial knowledge, we have analyzed and characterize those knowledge that are mobilized in the different critical activates related to each sensitive process. We have often called to model the creation process of each of these knowledge. Table 4 illustrates the result of the in-depth analysis of the knowledge relative to “the choice of material”. To assure good choice of material, the filtration system needs to be efficient whatever the rolling system. The choice of the material includes the constraints relative of the engine working, implementation and storage of residue.

Table 4. Analysis of the knowledge relative to “the choice of material”

Knowledge	Used in	Tacit/explicit dimensions	Production time	Validity
Knowledge relative to the choice of material structure”	Design and methodology relative to the calibration of filter reactivation	- 70% : Explicit(e.g. in technical documents) - 30% : explicitable	2 years	Validated through experimentations

2) Step 2. Construction of criteria and evaluation of “knowledge of reference”: Three sub-families of criteria where constructed (see the Appendix): (i) *knowledge vulnerability family* including the eight criteria $g_1,\ldots,g_8$ in the Appendix that are devoted to measure the risk of knowledge lost and the cost of its (re)creation; (ii) *knowledge role family* including the criteria $g_9,\ldots,g_{14}$ in the Appendix that are used to measure the contribution of the knowledge in the project objectives. The criteria

$g_9,\ldots,g_{14}$ are specific to the FAP project and should be replaced by other ones for other projects. These criteria correspond to the objectives in the contribution degree computing model and (iii) *it use duration family* including the criterion g_{15} in the Appendix that is devoted to measure the use duration of the knowledge basing on the company average and long term objectives.

Once criteria family is constructed, we need to evaluate each knowledge of reference in respect to all criteria. We have distinguished three family of criteria which permit to measure the vulnerability of the knowledge and implies criteria g_1, g_2, g_3, g_4, g_5, g_6, g_7 and g_8; the role of each knowledge in each objective and implies criteria g_9, g_{10}, g_{11}, g_{12}, g_{13} and g_{14}; and use duration of each knowledge which implies criterion g_{15}.

- As mentioned earlier, the evaluations of "knowledge of reference" in respect to criteria g_1, $g_2,\ldots,g_8$ are provided by the decision makers. For example, in respect to criterion complexity, the knowledge "relative to different characteristics that exist between FAP command law and the other CMM command laws" is considered as "very complex" since this knowledge depends on several other knowledge related to the law of EGR (Exhaust Gaz Recirculation) command, the law of CAN (Controller Area Network) command, the law of gearbox command, to the injection system and to the law of FAP command. The knowledge "relative to different characteristics that exist between FAP command law and the other CMM command laws" is considered as "low accessibility" since this knowledge is gathered by only one expert; who is overburdened with work.
- The evaluation of knowledge of reference in respect to criteria g_9, $g_{10},\ldots$, g_{14} are evaluated through model presented in [22] [21].
- The evaluation concerning criterion g_{15} is provided by experts. For example, the knowledge relative to "the measurement of the additive" has an average use duration because is related to the use duration of the first generation FAP system; new generations of the FAP systems are without additive.

3) Step3. Inference of decision rules: To infer rules, we have constructed four decision tables containing the evaluations of 34 "knowledge of reference" in respect to 15 and to the assignment examples provided by four decision makers.

We present in Table 5 an extract from the decision table concerning the assignment of three knowledge of reference";

- "K_8: knowledge relative to proportion of the additive";
- "K_9: knowledge relative to the performance of oxidation catalyst"; and
- "K_{16}: knowledge relative to material of filter support" provided by one decision maker.

Table 5. An extraction from the decision table for one decision maker

K_i	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}	g_{11}	g_{12}	g_{13}	g_{14}	g_{15}	Decision
K_8	2	2	3	3	1	2	4	4	5	2	4	5	5	5	2	1
K_9	3	3	2	2	3	3	4	4	4	2	4	4	3	4	2	1
K_{16}	2	3	3	2	2	2	3	4	5	2	5	5	5	2	2	2

First, each decision maker selects the decision rules. We have applied the DOMLEM algorithm, proposed in DRSA method to infer rules permitting to characterize knowledge assigned to classes Cl1 and Cl2. The set of decision rules identified by decision maker r permit to establish Table 6. The result obtained are traduced in the form of approximation quality, and permitted us to verify the presence of inconsistences in the decision rules. These rules are deduced from the comparison of information related to the assignment examples intuitively provided by each decision maker, and the assignment generated by the algorithm. To illustrate the incoherence, we consider the assignment of a given decision maker *r*. Initially, decision maker *r* assigns K_{11}, K_{14}, K_{15}, K_{16} and K_{21} simultaneity to Cl1 and Cl2. Thus, we have called this decision maker to carefully reconsider the evaluation of each of these knowledge. Concerning knowledge K_{11} and K_{15}, the decision maker mentioned that hesitated when he assigned these knowledge. For knowledge K_{14}, K_{16} and K_{21}, there is no remark and we do not modify his/her assignment. We have reviewed with all the decision makers that have provided inconsistent decision rules and that are ready to modify his/her assignment examples.

Table 6. Approximation qualitative decision maker *r*

Decision Class	F-lower approximation	F-upper approximation	F-Boundaries of sets Cl1 and Cl2	Approximation quality
Cl1 : “at most non crucial knowledge”	K1, K2, K8, K9, K17, K23, K28	K1, K2, K8, K9, K11, K14, K15, K16, K17, K21, K23, K28	K11, K14, K15, K16, K21	0.58
Cl2 : “at least crucial knowledge”	K3, K4, K5, K6, K7, K10, K12, K13, K18, K19, K20, K22, K24, K25, K26, K27, K29, K30, K31, K32, K33, K34	K3, K4 K5 K6 K7 K10 K11 K12 K13 K14 K15 K16 K18 K19 K20 K21 K22, K24, K25 K26 K27 K29 K30 K31 K32 K33 K34	K11, K14, K15, K16, K21	0.81

Once each decision makers chooses the decision rules relatives to different assignment examples, we determine, jointly with the decision makers, a subset of decision rules that permit to evaluate the crucial knowledge. Three examples of jointly selected decision rules follows (expressed in mathematical form):

Rule 1: If $g_3(k) \geq 3 \wedge g_6(k) \geq 2 \wedge g_9(k) \geq 5 \wedge g_{15}(k) \geq 2$ Then $x \in Cl_2^{\geq}$

Rule 2: If $g_3(k) \geq 2 \wedge g_6(k) \geq 2 \wedge g_{12}(k) \geq 4 \wedge g_{15}(k) \geq 2$ Then $x \in Cl_2^{\geq}$

Rule 3: If $g_1(k) \geq 3 \wedge g_3(k) \geq 2 \wedge g_8(k) \geq 4 \wedge g_{15}(k) \geq 2$ Then $x \in Cl_2^{\geq}$

In the system, Rule 2 is traduced as follows:

IF K_i. Substitutable –Level is "at least weak"
and
K_i. Rarety-Level is "at least rare"
and
K_i. Competitivity is "at least high"
and
K_i.use-duration is at least "average"
THEN K_i is at least in *Cl2*

This rule means that a piece of knowledge K_i is considered crucial (i.e. K_i belongs to the class of at least crucial Cl2), if it is difficult to replace it, it is scares, have an important impact on commercial position of the company and also has convenient use duration.

5.3 Phase 3: Classifying potential crucial knowledge

In this phase, the system use decision rules defined in the first step to assign new "potential crucial knowledge" to either Cl1 or Cl2. Those assigned to Cl2 are the crucial ones that need to be capitalized on.

1) Step1. Definition of a "potentially crucial knowledge" set: First, we have identified, with the help of the stakeholder, the decision makers implied in this second phase. There are 6 implied decision makers. These are the ones that have participated to phase one plus the responsible on the cooperation with another automobile constructor company. With all these decision makers, we have first retained all the knowledge that are supposed potentially crucial and than we have combined some ones (that they find very detailed) and removed/added some another ones. The final list is obtained after individuals discussion with the different decision makers and validated through emails with all of them. The choice of the set is facilitated by the analysis of process and activities performed during the definition of knowledge of reference process. For example, the knowledge relative to re-dimensionnement engine control calculator have been considered to be potentially crucial.

2) Step2. In-depth analysis of potentially crucial knowledge: we have applied for each potentially crucial knowledge the same process as applied in step 2 of phase 1.

3) Step 3.Evaluation of potentially crucial knowledge: We have evaluated all potentially crucial knowledge in respect to all criteria constructed in step 3 of phase 1. The obtained performance table contains the evaluation of each potentially crucial knowledge in respect to criteria related to:

- The vulnerability of knowledge (i.e g_1, g_2,g_3, g_4, g_5, g_6, g_7,g_8) ;
- The role of knowledge for each objective (i.e. g_9, g_{10},g_{11}, g_{12}, g_{13}, g_{14}) ; and
- Use duration (i.e g_{15})

Table presents an extract from the performance table.

4) Step 4. Application of decision rules:

We have used the performance table containing the evaluation of different knowledge of reference as input in this phase. Thus, it will be required only one rule (that characterize knowledge required a capitalizing operation) is verified to conclude that the knowledge is crucial.

6 Conclusion

In this paper we have presented a generalized method to make GAMETH usable for any complex project. We have developed a novel methodology that constructs the set of "crucial knowledge". This methodology consists of three phases. During the first phase, decision rules are inferred, through rough sets theory, from decision assignments provided by the decision maker(s). It includes the identification of a set of "reference knowledge" and its evaluation with respect to a convenient set of criteria. In the second phase, a multicriteria classification of "potential crucial knowledge" is performed on the basis of the decision rules that have been collectively identified by the decision maker(s).

Several points related to the methodology itself need to be investigated:

- *The contribution degrees model* should take into account evolution of different industrial projects concerned by the capitalization operation. For example, during our experiences at automobile company, some data relative to the use of a chemical substance in the FAP system were qualified as very important by the actors, and hence the corresponding knowledge were computed as important by the model. Eight months later, this substance is not used any more in the project. One possible solution to tackle this problem is to use robustness analysis [18]. More precisely, this type of uncertainty may be modelled in terms of scenarios corresponding to the possible combinations of different values attributed by each actor to the contribution of each knowledge to each objective.
- *Enhancing the K-DSS with fuzzy logic*: to enhance the capabilities of our system, we propose an ongoing work aiming to take into account imprecision and uncertainty at the database level. Fuzzy set seems to be a natural way to cope

with this problem. Indeed, class Knowledge may be defined as fuzzy concept with two extent properties: $P_{knowledge} = \{p_1, p_2\}$ where p_1 and p_2 are based on level-of-tacit and degree-of-maturity attributes, respectively, these two attributes are not defined in the original model. By associating appropriate weighs w_1 and w_2 to the extent proprieties p_1 and p_2, the degree of membership of a piece of knowledge K_i to fuzzy class Knowledge may be computed as follows:

$$\mu_k(K_i) = \frac{\sum_{i=1}^{n} \rho p_k^i(v_i).w_i}{\sum_{i=1}^{n} w_i} \quad . \tag{4}$$

where the number v_i is the value of the attribute of K_i on which the extent property p_i is defined and $\rho p_k^i(.)$ represents the extent to which entity K_i verifies property p_i of fuzzy class K. The idea may easily be generalized to other classes of the model.

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Appendix: List of criteria

Criterion	Description	Scale	Preference
g_1 complexity	measure the level of complexity of knowledge	- non complexe - complex - very complex	↑
g_2 accessibility	measure the level of accessibility of the knowledge	- easy - average - difficult	↑
g_3 substituability	measure the level of substituability of the knowledge	- non substituable - weakly substituable - substituable	↓
g_4 validation type	indicates the way the knowledge is validated	- numerical simulation - experimental - experimental and numerical simulation	↑
g_5 transferability	measures the level of transferability of the knowledge	- easily - averagely - hardly	↑
g_6 rarety	measures the level of rarety of the knowledge	- not rare - rare - very rare	↑
g_7 acquisition cost	measures the cost of production of the knowledge	- low - average - high - very high	↑
g_8 acquisition time	measures the time required to acquire and/or produce the knowledge	- short - average - high - very high	↑

g_9 impact on product cost	measures the impact of the knowledge on minimizing the cost of product	- no impact - very low - low - average -high -very high	↑
g_{10} impact on product developing	measures the impact of the knowledge on minimizing the development cycle of the product	- no impact - very low - low - average - high -very high	↑
g_{11} impact on system integration	measures the impact of the knowledge on ameliorating the integration of the FAP system in the vehicle	- no impact - very low - low - average - high - very high	↑
…			
g_{14} impact on system fiability	measures the impact of the knowledge on ameliorating the fiability of the FAP system	-no impact - very low - low - average - high - very high	↑
g_{15} use duration	measures the use duration of the knowledge in the company	- short - average - high	↑