

Multi-Model for Planning High Complexity Spectrum

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Abstract: The objective of this papere is to contribute to a planning policy in the innovation value chain in the perspective of the technology development process – TDP. Therefore, a multi-model reference proposal was created based on the definition of high complexity spectrum strategies, which considers a sequence of systematic procedures in the following phases: Phase (i) determine the information needs, phase (ii) determine the actors' knowledge in the innovation value chain, phase (iii) determine the degree of knowledge evaluation, and phase (iv) determine the strategies in innovation value chain in the technologies development process. The study shows thes application of this process in high tech based companies in Brazil. Several support tools were used to formulate the modeling in order to reduce subjectivity in the results: psychometric scaling – Thurstone's Law of Categorical Judgments (LCJ), Multicriteria Analysis-Compromise Programming, Electre III and Promethee II, Artificial Neural Networks (ANN) and Neurofuzzy Technology. The mains results obtained demonstrated that

Keywords: Multi-model; Planning; high complexity spectrum.

I INTRODUCTION

Recently, relevant changes have made organizational boundaries more fluid and dynamic in response to the rapid pace of knowledge diffusion [1];[2];[3];[4], and innovation and international competition [5]. This helps to reconsider how to succeed with innovation ([3] [4]; [5]). Thus, innovative companies make use of their capabilities to appropriate the economic value generated from their knowledge and innovations [2],[3],[4]. Therefore, the supply of innovative products is presented as a quality standard in the race for pressing demands.

It is believed that industries that can offer their products to customers more efficiently and faster will probably be in a better position to create a sustainable competitive advantage [6] due to knowledge and innovation [3], [4]. In this dichotomy, technical efficiency is a parameter of the developing capacity of innovative products, which translates into one of the most remarkable logical arguments to potentialize and encourage competitive advantage [6]. One of the main challenges is to develop products in high complexity environments. Solutions to these challenges have been offered by the companies' equally innovative technical capabilities, greater efficiency, productivity and high quality [6].

It is true that a new product / technology or process can represent the end of a series of knowledge initiatives and the beginning of a process of value creation, which, under conditions imposed by various parties, can produce efficient results in the global performance of the value chain, reaching not only businesses that innovate, but also correlated companies [7], [8]. Knowledge can lead to performance improvements of other co-related or co-located industries [7]. Moreover, innovations are the incremental results produced by the interaction process of the knowledge generated, disseminated and applied to the various links in the value chain [9], [10], [11], in which the first link of the innovation value chain is the knowledge derived from the companies' various sources. The second link of the innovation chain value is the transformation of knowledge into product and process. The final link in the innovation value chain is the knowledge that is exploited. This is the process by which business performance is influenced by innovation. It is the utilization of products by the companies – and the main focus is business return and growth. Of course knowledge goes beyond the company's boundaries and links in the value chain and influences the results of the innovation value chain.

The value chain management – VCM has for quite some time presented challenges within a wide diversity of extremely complex events, all of which in an unsure and risky context that can affect the flux of decisions and the desired levels of performance, hence frustrating expectations for stability. It must be acknowledged that risks can be brought about from different origins and scenarios. With time, this eventually leads to changes in the configuration of the chain. Consequently, it is considered one of the main challenges of innovation value chain management, which basically consists of creating integrated structures of decision making in an extensive universe containing multiple organizations. This requires an integrated and shared decision structure that involves key business processes, concerning efficient coordination of functional-temporal company-client [12], [13] [14], [15].

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The characteristics of the value chain differ a great deal, therefore becoming the object of analysis equally differentiated. The good practice recommends fulfilling a sequence of articulated actions, which consist of the following phases: (i) planning the necessities; (ii) institutionalization and formation of a project team and determination of the communication procedures; (iii) the objectives' consolidation, results and performance's goal of the value chain; (iv) study of the costs, prescriptions, flows of box; (v) study of the social impacts; (vii) analysis, allocation and management of risks (preliminary evaluation), etc. Many times the projects are made impracticable still in the act of planning, hence becoming unsustainable. One of the aspects that deserves to be highlighted is the occurrence of errors in the management of the value chain, which often results in a non-fulfillment of the established goals and performance. It is imposed thus that the efficiency in the planning of the value chain propitiates more efficient decisions, diminishing the improvisation and improvement of the involved team. Traditionally, the planning phase "sins" when it is elaborated without support of methods and adequate techniques having prioritized the knowledge that really is essential in the management of the innovation value chain. In this spectrum, the perspective of the efficiency of the innovation value chain management should be standardized in methods and techniques which permit a correct planning and management upon the decisions to be made.

This process should result in people with adequate knowledge to perform tasks correctly at the right place and opportune moment [16]. The knowledge may represent a strategic tool, increasing the institutional capacity of the Entrepreneurs in their assignments of formulation, evaluation and execution of such projects [17], [18], [19], [20]. The knowledge would work as a facilitator instrument of improvement, contributing for the quality of services and the enhancement of the agility to decide. Monitoring the performance of innovation value chain from a knowledge perspective requires that the appropriate monitoring procedures are in place and operational [17], [21], [22]. Generally, a keen eye must be kept on the knowledge household of innovation value chain. Especially important is watching the external environment for new events that may have impacts on the way innovation value chain. In order to improve the performance of the entire innovation value chain, it is necessary to cross the boundaries of individual companies and consolidate the entire chain, in other words, a cohesive and integrated system to increase the chain's knowledge flow.

Generally, the VCM models are usually developed by conventional modeling techniques, including mathematical programming, simulations, heuristics and statistical and probabilistic tools. However, none of these planning and managing models listed by the literature investigated takes into consideration the priority of cognitive elements in the innovation value chain management. The objective of this papere is to contribute to a planning policy in the innovation value chain in the perspective of the technology development process – TDP. Therefore, a multi-model reference proposal was created based on the definition of high complexity spectrum strategies, which considers a sequence of systematic procedures in the following phases: Phase (i) determine the information needs, phase (ii) determine the actors' knowledge in the innovation value chain, phase (iii) determine the degree of knowledge evaluation, and phase (iv) determine the strategies in innovation value chain in the technologies development process. The study shows thes application of this process in high tech based companies in Brazil. This work is systematized in the following sections: 1- The Method, and 2 - The conclusions and implications.

II. THE METHOD

The current proposal to build up a methodological support applied to the innovation value chain management happens within the following proceedings: *Phase 1:Modeling the Information Needs; Phase 2: Modeling Knowledge; Phase 3: Determining Degree of Knowledge Evaluation; Phase 4: Modeling the Network Strategies; Phase 5: Modeling the Network Strategies; Phase 6: Determining the DAKE - Conclusion of the TDP. Next, the detail of the phases and steps.*

Phase 1: Modeling the Information Needs This phase is subdivided into: *Step 1: Modeling the CSFs; and Step 2: Modeling the information areas*

Step 1: Determination of CSF. This phase is focused on determining the CSF, and is itself structured in two stages: Identification of CSF and (B) evaluation of CSF.

(A) *Identification:* The identification of CSF is based on the combination of various methods (Liedecker and Bruno,1984): (a) environmental analysis (external variable: political, economical, legislation, technology and among others.); (b) analysis of the industry structure (users' needs, the evolution of the demand, users' satisfaction level, their preferences and needs; technological innovations); (c) meeting with specialists and decision makers; and (d) the study of literature. The result has allowed defining four groups that represent the CSF:Market factor; Governmental Public Policies factor; Economical and Financial factor; and Technical factor.



(*B*) *CSF Evaluation:* After their identification, the CSF are evaluated in order to establish a ranking by relevance. Here the scale model of categorical judgments designed by Thurstone in 1927 has been adopted. This model starts form mental behavior to explain the preference of a judge (individual) concerning a set of stimuli $\{O_1, O_2, ..., O_n\}$. Thus, the evaluation of the CFS is systematized in the following steps: Step 1: determination of the frequencies by pairs of stimuli. Step 2: determination of the frequencies of ordinal categories. Step 3: calculation of the matrix $[\pi ij]$ of the relative frequencies accumulated. It is highlighted though that the results to be achieved in Step 3 reflect the probabilities of the intensity of the specialists' preferences regarding the stimuli, the Critical Factors of Success in this work. As a result, a hierarchical structure of CSF is obtained. Assembling here the many dimensions of the CFSs, the results show that there are:: first, the Market factor; second, the political factor; third, the Economical and financial factor; fourth, the Technical factor.

Step 2: Identification of the Areas of Information. The CSF having already been defined, information areas are delimited with respect to the different CSF. The CSF having already been defined, the information areas are delimited with respect to the different CSFs. After determining the CSF, the determination of the areas of information ensues. The result has allowed defining four groups that represent the areas of information: first, the Market Área; second, Governmental Area on Public Policies; third, the Economical and Financial Area; fourth, the Technical Information Area. The goals of the areas of information define specifically what must be achieved by these areas to meet one or more objectives from the projects (business), contributing for the enhancement of the project performance as to quality, productivity and profitability.

Step 3: Prioritization of the information needs starting from the crossing of CSF and the Areas of Information.

Again, these information areas are ranked by application of the same Categorical Judgment Method of Thurstone (1927) and put into relation with the CSF. At this moment the following tools have been adopted: (a) Multi-objective utility – multi-attribute, in this case Compromise Programming TM, which represent mathematically the decision makers' preference structure in situations of uncertainty; (b) selective, taken on account for the situation, Promethee II TM and (c) Electre III TM. These methods rendered their contributions in determining the performance in the areas of information, which led to the identification of Market Area as the most important ones in order to globally ensure the overall critical success factors. Aiming to know which area of the innovation value chain management the decision makers must develop a "strong management", the prioritization of information needs takes place. The results shown by the Methods Compromising Programming, Electre III and Promethee II have pointed out the market Area as the most relevant one to guarantee the CSF. The critical knowledge for innovation value chain management is determined in the sequence.

Phase 2 Modeling Knowledge on Innovation Value Chain

This phase has been subdivided as follows: This phase has been subdivided as follows: *stage 1 - identification* and acquisition of knowledge; and stage 2 - evaluation of knowledge. This proceeding is shown in details as to its structure.

Stage 1: Identification and Acquisition of Knowledge. Initially, information topics which have been already identified will be elaborated, analyzed and evaluated in order to be understood by the decision makers during the formulation and the management of a TDP project. Following this, they will be reviewed and organized and validated by TDP specialists. Afterwards, relevant theories and concepts are determined. With respect to the acquisition procedures, the different procedures of the process of acquisition represents the acquisition of the necessary knowledge, abilities and experiences to create and maintain the essential experiences and areas of information selected and mapped out [23].

Acquiring the knowledge (from specialists) implies, according to [24], the obtaining of information from specialists and/or from documental sources, classifying it in a declarative and procedural fashion, codifying it in a format used by the system and validating the consistence of the codified knowledge with the existent one in the system. Therefore, at first, the way the conversion from information into knowledge is dealt with, which is the information to be understood by and useful for the decision making in projects on TDP. First the information is gathered. Then the combination and internalization is established by the explicit knowledge (information) so that it can be better understood and synthesized in order to be easily and quickly presented whenever possible (the information must be useful for the decision making and for that reason, it must be understood). In this work, we aim to elaborate the conversion of information into knowledge.

The conversion (transformation) takes place as follows: first, the comparison of how the information related to a given situation can be compared to other known situations is established; second, the implications brought about by the information for the decision making are analyzed and evaluated; third, the relation between new knowledge and that accumulated is established; fourth, what the decision makers expect from the information is checked. The conversion of information into knowledge is assisted by the information maps (elaborated in the previous phase by areas, through analysis and evaluation of the information). We highlight that the information taken into account is both

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the ones externally and internally originated. The information from external origins has as a main goal to detect, beforehand, the long-term opportunities for the project. The internal information is important to establish the strategies, but it has to be of a broader scope than that used for operational management, because besides allowing the evaluation of the performance it also identifies its strengths and weaknesses. Following from this, the proceedings for the acquisition of theoretical background and concepts are dealt with.

Such proceedings begin with the areas of information, one by one, where the concept and the theory on which is based the performance of the actions (articulations) developed in those areas that allow to guarantee the feasibility of the projects on innovation value chain management are identified. In other words, which knowledge and theory are required to be known in order to ensure the success of projects on innovation value chain management in that area. Then, the analysis of surveys in public and private institutions about the job market for these institutions takes place bearing in mind the demands of similar areas studied in this work. As for the offer, we intend to search for the level of knowledge required by the companies and other organizations in those areas, as well as what concerns technical improvement (means) for the professionals. This stage determines the concept of knowledge to be taken into account on the development of this work. So, for the operational goals of this work, we have adopted them as the "contextual information" and the theoretical framework and concepts. After being identified and acquired, the knowledge is evaluated, with the aid of the Method of Categorical Judgments of [25] and artificial neural network (ANN). *Evaluation for the method Categorical Judgments' Laws (1)*

The achievement method of the research results with the specialists of innovation value chain, who revealed their preferences for pairs of stimulation (in the case, the objects of knowledge, and these submitted the ordinal categories $C1 = 5^{\circ}$ place, $C2 = 3^{\circ}$ place and $C3 = 4^{\circ}$ place). The evaluation of objects of knowledge (LJC) happened in three stages: In the stage (1), one determined the frequencies for pairs of stimulations, where Oi is equivalent to objects of knowledge and Oj the specialists. The data had been extracted from the preferences of the specialists in relation to objects of knowledge, attributing weights to the cognitive elements. After that (stage 2), the preferences of the specialists are determined in relation to the stimulations (knowledge). The results were obtained by means of the ordinal frequencies from the results of the previous stage. Finally (stage 3), the accumulated relative frequencies were calculated first. The results obtained here reflect the probabilities of preferences intensity of the specialists in relation to the stimulations (knowledge). The result of the preferences. In order to demonstrate the application of the methodological proposal, the results of the objects of knowledge on the "Market Area" were dealt (Table 1).

TABLE 1:

OBJECTS OF KNOWLEDGE (THEORETICAL BASES AND CONCEPTS AND CONTEXT INFORMATION) ON THE MARKET AREA

Theoretical Bases and Concepts and Context Information – Market Business						
Knowledge (Stimulis)	C1	C2	C3	C4	Total	Ranking
Project management of technology	-1,22067	-1,2207	-1,221	-0,7647	-4,43	1°
Engineering knowledge and information technology	-1,22064	-1,2206	-0,14	1,22064	-1,36	7°
Suppliers of products and technologies	-1,22064	0,43073	1,2206	1,22064	1,651	10°
Modeling	-0,76471	-0,4307	1,2206	3,86499	3,89	13°
Economy	-1,22067	-1,2206	-0,765	1,22064	-1,99	5°
Teory Policy	-0,76471	0,43073	1,2206	0,76471	1,651	10°
Partnerships and alliances	-1,22064	-1,2206	-0,431	1,22064	-1,65	6°
Demand for products and technologies	-1,22067	-1,2207	-1,221	0,43073	-3,23	3°
Competitive strategy	-1,22067	-1,2206	0,4307	1,22064	-0,79	8°
Organizational structure of technological projects	-1,22067	-0,7647	0,1397	3,86499	2,019	11°
Institutionalization of technological projects	-1,22067	-1,2206	1,2206	3,86499	2,644	12°
Planning and technologies management	-1,22067	-1,2206	-0,14	3,86499	1,284	9°
Risks in projects of technologies	-1,22067	-1,2207	-1,221	-0,1397	-3,8	2°
Quality and productivity in technological projects	-1,22067	-1,2206	-0,765	0,43073	-2,78	4°

Evaluation of Knowledge's Objects using the artificial neural network (ANN) (2)



The artificial neural network (ANN) is understood to simulate the behavior of the human brain through a number of interconnected neurons. The ANN has the capacity to recognize and to classify standards by means of processes of learning and training. The training of the net is the phase most important for the success of the applications in neural network. The topology of the net can better be determined of subjective form, from a principle that consists of adopting the lesser intermediate number of possible layer and neurons, without compromising the precision. Thus, in this application, the layer of the entrance data possess 15 neurons corresponding the 15 variable referring to objects of knowledge. The intermediate layer possesses 7 neurons, and the exit layer possesses 1 corresponding neuron in a scale value determined for the ANN. The process of learning supervised based in the Back propagation algorithm applying software Easy NN determines the weights between the layers of entrance and intermediate, and between the intermediate and exit automatically.

The training process was finished when the weights between the connections had allowed minimizing the error of learning. For this, it was necessary to identify which configuration that would present the best resulted varying the taxes of learning and moment. After diverse configurations to have been tested, the net of that presented better resulted with tax of an equal learning 0,30 and equal moment 0,80. The data had been divided in two groups, where to each period of training one third of the data is used for training of net and the remain is applied for verification of the results.

After some topologies of net, and parameters got the network that better resulted had presented. The net was trained for attainment of two results' group for comparison of the best-determined scale for the networks. In the first test the total of the judgment of the agents was adopted, however only in as test was gotten better scales, next of represented for method of the categorical judgments. With this, the last stage of the modeling in ANN consisted of testing the data of sequential entrance or random form, this process presented resulted more satisfactory. The reached results had revealed satisfactory, emphasizing the subjective importance of scale's methods to treat questions that involve high degree of subjectivity and complexity. How much to the topologies of used networks, the results gotten of some configurations of the ANN and compared with the CJT, were observed that ANN 1, is the one that better if approached to the classification gotten for the CJT. Thus, even other topologies do not Tenaha been the best ones, it had been come however close in some objects of knowledge of the CJT. The results can be observed in Figure 1 that follows.



Fig.1: Priority of Knowledge's Objects - ANN and CJT

The prioritized objects for the tool proposals were for innovation value chain management knowledge. Artificial Neural Networks (ANN), as well as Psychometric (CJT), was restricted only to the specialists' decisions in projects of raised subjectivity and complexity, needing other elements that consider the learning of new knowledge. However, it is interesting to highlight that the CJT method, as it considers a variable involving a high degree of subjective and complexity and because it works with probabilities in the intensity of preferences, considers the learning of new elements of knowledge. Thus, it can be said that for typology of application, as presented here, it is sufficiently indicated.

Phase 3: Determining Degree of Knowledge Evaluation:

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The results generated in this phase define the modeling strategy standards in this knowledge network (innovation value chain), which will be elaborated in the next phase. The strategy modeling results from the variation between the degrees of knowledge (Desired - D and - Real - R) developed at this stage, in two steps: (i) determining DDKE – Degree of Desired Knowledge Evaluation for performing the activities and actions considered by the AIs. 2) Determining DRKE – Degree of Real knowledge evaluation. The actual knowledge is the knowledge the individual has at the moment preceding the technology development process.

Step 1: Determining DDKE: The neurofuzzy technology will be applied to obtain DDKE (Figure 2), which is a credible and feasible modeling tool, structured according to the analogy of Cury's model developed in 1999, with hierarchical architecture, which brings together the experts' degrees of evaluation (previous estimates), with the interaction of all the data in inference blocks that uses fuzzy rules and verbal expressions, resulting in knowledge evaluation by means of weighting, which produces the degree of knowledge evaluation (DKE) [26], [27], [28]. The neurofuzzy technique was chosen due to the high subjectivity of the variables in the process and the relevance of the decision maker's opinion, which is an appropriate method for this application, as it allows the interaction of variables converged into a single evaluation parameter [26], [27], [28]. Under this proposal, the model is systematized according to the steps: (i) definition of input variables, (ii) definition of the inference system, and (iii) definition of the output variables (Figure 2). These steps are detailed to follow.



Fig. 2: Neurofuzzy Model - DDKE

Architecture of the Neurofuzzy Network: In each network node, two or more elements are assembled in one single element, originating a new node. This new node is then added to other nodes, produced in parallel, which give rise to a new node. And so on, until the final node is attained. The neurofuzzy network architecture (NNA) is defined by the input variables in its first layer, always converging to their network nodes. Each node corresponds to a fuzzy rule base, designated as Inference Block (IB), in which the linguistic variables are computed by aggregation and composition in order to produce an inferred result, also in the linguistic variable form. Thus, the rules are defined in the IB of NNA. In summary, the input variables (IV) pass through the fuzzification process and through the inference block (IB),



producing an output variable (OV), called the intermediate variable (IVa), if it does not correspond to the last IB in the network. This IV, then joins another IV, forming a set of new IVs, hence configurating a sequence in the last network. In the last layer, also composed of IV, it produces the output variable (OV) of the final NNA. This OV then undergoes the defuzzification process so that the final result is obtained in the DDKE analysis. The NNA architecture should be applied according to the number of specialists. These steps are detailed below.

Sub-step 1: defining the input variables

The structure of the method helps to extract the experts' perceptions about the minimum knowledge required (DDKE) for the performance of activities and actions in AI (application object). The IVs that interfere in the process, as previously referenced, are identified and evaluated in the previous phase with the intervention of the experts. A representative sample of experts is recommended. These IVs, which are: knowledge transformed into linguistic variables, with their respective degrees of certainty or conviction (GDC), depending on the interaction between the experts, based on fuzzy¹ sets and on the IF-THEN rules. This phase is called fuzzification, since it uses the fuzzy sets for such conversions. The GDCs are defined subjectively, based more on pragmatism than on statistics. The variables are qualitative and the linguistic terms are assigned to each IV: High, Medium and Low. Each IV must be characterized and should have defined numerical or linguistic values. And the lack of measures for the qualitative IVs can be accommodated by converting the observation fields into linguistic variables, by assigning, according to the experts' perception of evaluation degrees, a 1 to 10 scale, using an instrument (Form or Questionnaire). The IV undergoes the fuzzification process, according to the numerical scores that reflect the experts' feelings. Thus, the generic fuzzy sets should be defined for all qualitative IVs, which always have three levels of linguistic terms: a lower, middle and superior level. The construction of these fuzzy sets is based on the experts' representative sample, who assign linguistic terms to all the scores of the 1 to 10 scale, within a generic context. In short, the input variable is used, whose linguistic terms are: High, Medium, Low, and the expert is asked to assign a score (0 to 10 scale) to the study object (weighted by importance). Next, the fuzzification process of the qualitative variable takes place. In summary, once the IVs and their linguistic terms are defined, they are input into the neurofuzzy inference system network, hierarchically created, using the IF-THEN rules, thus providing evidence to the degree of knowledge evaluation (DKE) through a final linguistic variable, which through a linguistic defuzzification process indicates the previous DDKE.

In summary, based on data collected in Phase 2 (identification and capture of the knowledge objects), to achieve this step, the top 15 knowledge classifications were selected to feed the input variables in this Phase and Step. For example (hypothetical), when the expert's opinion was solicited about which desired degree of technical knowledge the product development manager (technology-based company) should have, the answer was 7.0. Next, the fuzzification process (simulation) took place, assigning the linguistic terms: LOW, MEDIUM and HIGH levels of evaluation on a 1 to 10 scale. For score 7, considered LOW by 0% of the specialists, MEDIUM by 55% and HIGH by 45% (Table 2).

FUZZI SEIS-IV TECHNICAL KNOWLEDGE DESIKED											
Experts	Linguist terms	Degree of knowledge									
		1	2	3	4	5	6	7	8	9	10
1	LOW										
	MEDIUM										
	HIGH										
2	LOW										
	MEDIUM										
	HIGH										
3	LOW										
	MEDIUM										
	HIGH										
20											
	LOW	100	100	55	25	0	0	0	0	0	0
Degrees of	MEDIUM	0	0	35	75	100	90	55	40	0	0
certainty (DoC) (%)	HIGH	0	0	0	0	0	10	45	70	100	100

TABLE 2:					
FUZZY SETS – IV TECHNICAL KNOWLEDGE DESIRED					

With the specialists' responses the degree of certainty of linguistic terms in each of the input variables was determined using the fuzzy sets. The generic fuzzy sets were defined for all the qualitative IVs, which always have three levels of linguistic terms: a lower, middle and higher level (Table 3).



	TABLE 3:						
GENERIC FUZZY SETS FOR IVS – LINGUIST TERMS							
Knowledge	Characteristics	L	inguist term	S			
K. Technical	Qualitative	LOW	MEDIUM	HIGH			
k. Economical and	Qualitative	LOW	MEDIUM	HIGH			
Financial							
K. Market	Qualitative	LOW	MEDIUM	HIGH			
K. Policies	Qualitative	LOW	MEDIUM	HIGH			

Sub-step 2: Treatment of Intermediate Variables and Linguistic Terms

Once the IVs are defined, they undergo the fuzzification process and the inference block, hence producing the output variables (OV), called the intermediate variable (IVa), which then joins other IVs, forming a new set of IVs, therefore constituting a sequence until the last layer of the network. In the last layer, the definitive output variable (OV) of the Neurofuzzy Network is produced. This OV then undergoes the defuzzification process to obtain the final result.

The Fuzzy Inference corresponds to the fuzzy inference rules that consist of IF-THEN rules, which are responsible for the association of the input variables and generation of OVs in linguistic terms, with their respective pertinence functions. The rules constructed depend on the previous layer of IVs, and then generate the OVs. Based on the MIN-MAX operators, a linguistic vector of the IVs is obtained for the final OV of the method, whose linguistic terms were previously defined by the method. After converting all IVs into their corresponding linguistic variables, with their respective GDC, the fuzzy inference blocks (IB), composed of IF-THEN rules, are operated based on MIN-MAX operators, hence obtaining a linguistic value for each intermediate variable and for the output variable of the model, with the linguistic terms previously defined by the judges. With the input variables, the rule base is created. Each rule has an individual weighting factor, called the Certainty Factor (CF), ranging from 0 to 1, which indicates the degree of importance of each rule in the fuzzy rule base. And the fuzzy inference occurs from the rule base, generating the linguistic vector of the OV, obtained through the aggregation and composition steps. Table 4 shows the linguistic terms assigned to the intermediate variables.

TABLE. 4 : LINGUISTIC TERMS ASSIGNED TO THE INTERMEDIATE VARIABLES

Intermediate Variables	Linguistic terms				
Benefit Policies / Judicial	LOW	MEDIUM	HIGH		
Benefit. Market	LOW	MEDIUM	HIGH		
Benefit. Economical and Financial / Technical	LOW	MEDIUM	HIGH		
Performance Policies	LOW	MEDIUM	HIGH		
Performance Judicial	LOW	MEDIUM	HIGH		
Performance Market	LOW	MEDIUM	HIGH		
Performance Economical and Financial	LOW	MEDIUM	HIGH		
Performance Technical	LOW	MEDIUM	HIGH		

As a demonstration, Table 5 shows some linguistic vectors of the IVs and OVs, for the specialist.

TABLE 5:

LINGUISTIC VECTORS OF IVS – SPECIALIST						
Parameter	Linguistic terms	Degrees of certainty (DoC)				
Benefit Economical and Financial / Technical	LOW MEDIUM	2% 7%				
	HIGH	88%				
Benefit. Market / Policies	LOW	0%				
	MEDIUM	5%				
	HIGH	90%				

Sub-step 3: Treatment of Output Variable – Level of Knowledge Evaluation – DKE

The output variable (OV) of the Neurofuzzy model proposed was called Degree of Knowledge Evaluation – DKE. To enable the comparisons, the final output variable of the method, in other words, the linguistic vector of DKE must undergo the defuzzification process to be transformed into a real number, between 0 and 1. In defuzzification, the fuzzy system, when receiving an input, converts it into a fuzzy input, which is then submitted to the inference system (fuzzy rules) that returns a fuzzy output to this system. However, a numerical value in the output is desirable in many



cases. Defuzzification is not exactly the inverse process of fuzzification. Therefore, the fuzzy set, besides an X universe, is a set of orderly pairs represented by Equation 1.

$$A = \{(\mu_A(x), x) | x \in X\}$$
 (1)

Where $\mu_A(x)$ is a function of pertinence (or degree of pertinence) of x in A and is defined as the mapping of X in the closed interval [0,1], in agreement with Equation 2 [32].

$$\mu_A(x): X \rightarrow [0,1] (2)$$

The method proposed suggests the Center of the Maximum (CM) technique in the treatment of OV, which is one of the most widely used defuzzification techniques to transform a linguistic result into a numeric value again, according to [26], [27], [28], [29]. Most of the fuzzy logic systems use this step because the desired result often needs to be expressed in numerical form, rather than in the linguistic form. The DDKE value, which always belongs to the interval [0; 1], represents the experts' measure of preference intensity regarding the desired knowledge. For a DDKE equal to 1, the preference for knowledge is maximum, within the standards established in this method. On the other hand, for a DKE equal to 0, it means that this preference has no value in the expert's preference. In summary, the third and last stage of the fuzzy logic system, called defuzzification, translates the linguistic result of the fuzzy inference process into a numeric value [29] for comparison purposes. The Degrees of certainty (DoC) that determine the linguistic vectors resulting from the processes of aggregation and composition are defined by Equation 3.

GdC;:max[FC₁.min{ GdC_{A11} , GdC_{A12} ,..., GdC_{1n} },...,FCn.min{ GdC_{An1} , GdC_{An2} ,..., GdC_{Amn} }/(3)

In this case, after the fuzzy inference, a defuzzification process is required, that is, transform the linguistic values into numerical values from their pertinence functions [26], [27], [28], [29]. Usually, the Maximum Center method is used to determine an exact value for the Exit Variable linguistic vector. From this method, the certainty degree of the linguistic degrees is defined as "weights", associated to each of these values. The exact resolved value (RV) is determined by considering the weights in relation to the typical values (maximum values of the pertinence functions), in agreement with the definition of the Equation [29].

$$RV = \frac{\sum_{i=1}^{n} DoC_i \cdot X_i}{\sum_{i=1}^{n} DoC_i \cdot X_i}$$
(4)

Where DoC represent the degrees of certainty of the linguistic terms of the final output variable and X indicates the typical values for the linguistic terms that correspond to the maximums of the fuzzy sets, which define the final output variable. As a demonstration (hypothetical), attributing hypothetical degrees (average), the calculation of DDKEj is expressed with the GdCi of following linguistic vector of the output variable DDKE, also hypothetical: LOW = 0.25, MEDIUM = 0.44, HIGH = 0.12. The score of the numeric DDKE in a 0 to 1 scale corresponds to 0.6428, the result of the arithmetic mean of the scores resulting from the defuzzification of each of the twenty simulated judges. This score corresponds to an average value of DDKE. The following are the procedures for determining the previous DRKE of the members involved in TDP.

Step 2: Determining the participants previous DRKE

The methodological procedures were applied to five (hypothetical sample) members who participated in the TDP. The average of the results produced was then calculated. To know the level of knowledge of that team, a test with sixty closed-ended questions was applied, according to the four knowledge categories necessary for managing the product development projects. Based on the evaluation of the results, an adjustment in a 1 to 5 scale was performed, where 1 represents the minimum importance score or the knowledge domain and 5 represents the maximum score. Then, the mean and standard deviation of all participants were calculated. The results are shown in Figure 3.





Fig. 3: Mean and Standard Deviation of the knowledge- Political - P, Economic and Financial - E, Marketing - M, Technical -T

Combining the dimensions it can be stated that on average there is no predominance of one or another, with slight relevance to the market knowledge (M=3.64). And when analyzed internally, it was observed again that in the economic and financial group, there is a stronger preference for some knowledge objects (dp=1.13). In this perspective, regarding the values resulting from this preliminary analysis, at this stage the average size, the input variables for neurofuzzy modeling are considered, converging to DRKE. The result of this interaction for the actual knowledge produces the DRKE of the TDP team members on a scale of 1 to 10, which are the IV scores of the neurofuzzy system. The same procedures (architecture) were used in the DDKE calculation to achieve the DRKE.

For example (hypothetical), using the assigned degrees (average), we have the calculation of DAKEj with the GdCi of the following linguistic vector of the output variable DRKE, also an example: (LOW = 0.24, MEDIUM = 0.42, HIGH = 0.13). To find the numerical DRKE, there is the defuzzified score of the linguistic variable DRKE on a scale of 0 to 1. Thus, the DRKE shown corresponds to 0.5348. The three degrees of knowledge evaluation are compared (triangulation, - the previous degree of knowledge desired and degree of real knowledge versus post level of knowledge evaluation). This phase ends with the analysis and evaluation of the discrepancies between the degrees of knowledge and the proposed adjustments to model the strategies in the TDP innovation value chain. With the score results in this Phase, based on the specialized literature and the judges' intervention, the strategies (innovation value chain) are defined. The procedures are detailed in the next Phase.

Phase 4: Modeling the Network Strategies (innovation value chain)

In light of the results produced in the previous phase and based on the state of the art, a model is proposed to identify the strategies for the product development process in a high complexity spectrum (innovation value chain) according to the following phases: Phase (i) Analysis and evaluation of DDKE and GRKE, according to the intensity of their individual variations. Phase (ii) Survey of Strategies. The first phase will be through the experts' intervention and experience. However, the presence of Intelligent Agents as tools is recommended (in other applications) to facilitate understanding the environment and to perform information processing and knowledge tasks [30], to perform autonomous actions and to cooperate through intelligent mechanisms in order to achieve the intended objectives [31]. For this case, the intervention of experts in the process is satisfactory, considering the not very high number of participants. As a preparatory stage towards the definition of TDP strategies, it is necessary to identify the results produced by the variation between the desired and real personal knowledge, previously defined in the TDP. That is, before starting the product development process. Next, with the results, the experts use a judgment matrix to attribute weights according to the intensity of their preferences to prioritize strategies for the variation of the desired and real personal knowledge (previously) in the TDP. The intervention of experts is crucial in this process. With the results produced by DRKE (individual) and DDKE, both before the TDP, a judgment matrix (nature of the strategies versus knowledge) is produced, which has the experts' interference in the process, assigning weights to strategies based on the intensity of the degrees of knowledge. In other words, the experts assign weights to strategies according to the gap

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between the desired and real degree of knowledge. The strategies are always oriented toward DDKE. It should be noted that these strategies are confirmed on a permanent basis after consulting the experts, who assign weights according to the varying degree of knowledge evaluation. In this spectrum, the knowledge strategies are prioritized to achieve satisfactory TDP results.

The multicriteria analysis method was used as a decision support method. The development of strategies is structured according to the following analytical routine: Phase (i) defining the mission and purpose; Phase (ii) the structural analysis of the industry (innovation value chain); Phase (iii) selection of elements in the strategies; Phase (iv) definition of strategies and criteria for an effective strategy; Phase (v) development of strategies to supply the TDP knowledge network in technology-based companies; Phase (iv) adjustment of preferred strategies.

The following details the results produced in these phases. Phase to define the mission, to become a benchmark in the knowledge construction of the innovation value chain in the TDP - Brazil's high-tech industries by the integration and interaction of the individuals in a knowledge network, enabled by technology and other communication and information systems. Phase of the structural analysis of the industry (innovation value chain), according to the determinations proposed by Porter. Applying the SWOT analysis, we have: (A) Potential Internal Strengths: (i) technological skills; (ii) creative R&D management; (iii) strongly differentiated technology, (iv) strong team of experts, especially in content, few but with high potential experts; (v) basic competence in key areas; among others. (B) Internal Weak and Potential Points: (i) external potential opportunities: potential market and investment opportunities to expand nationally and globally; (B) Potential External Threats: Phase to select the elements in the strategies, schools, theories, other elements of the innovation value chain in TDP, from the literature and confirmed by the experts. The selection of these combined elements is then elaborated, which will help define the strategies. The strategies in the innovation value chain in TDP to be defined later are guided by the following Schools (quoted for [33]): (A) Design and Learning, focuses on dynamic capabilities; (B) Planning, focuses on scenario analysis; (C) Cognitive, focuses on constructivism; (D) Environmental, focuses on contingencies; and configuration, focuses on the process. Phase to define the strategies and criteria for an effective strategy. With the results produced in the previous phase, the following strategies were identified: (i) differentiation strategies: image, support, quality, design; (ii) customization strategies; (iii) package strategies; (iv) cognitive strategies; and (v) Learning.

In this spectrum, the following are defined as strategies: (*i*) *image differentiation strategies*, support, quality, design for: (a) environment; (b) technologies; (K) product; (d) interaction; (e) evaluation; (*ii*) package strategies, offer a range of products connected and integrated to form the complete package (innovative technology); (*iii*) cognitive strategies; (*iv*) learning strategies; and (v) customization strategies. The experts' judgment framework shows the strategies performed to secure the actors' knowledge and reach the intended objectives DDKE: (*i*) learning strategies; (*iii*) *image differentiation;* (*iv*) strategies for mass customization and; (v) support strategies; (vi) design differentiation strategies; (vii) package strategies, in that order, respectively.

Analyzing the internal logic of these strategies, the results produced show that the main image differences relate to the environment and evaluation of results (metrics). It is also vital to create efforts for the support strategies in the interaction methods and techniques and also technologies. The technology image is essential for customers, as it is observed that there is a greater chance of product rejection when it is perceived that the product is irrelevant or of little value for their needs. The evaluation must be perceived by consumers as a necessary tool and motivator in the knowledge construction process, which requires mapping during planning and defining the activities that fit each customer/client. In almost all interventions by the experts in the judging process of the strategies, most were emphatic in dealing with the dimensions interactions and motivations. However, all were unanimous in considering the set of strategies as equally important in the knowledge construction process.

Phase 5: Determining the DAKE - Conclusion of the TDP - Ex-Post

Under this proposal, an evaluation from the interaction of strategies in the knowledge network was performed (innovation value chain). This performance was operationalized by the neurofuzzy technology (the same procedure previously adopted for DKE), which integrates all the strategies. The result of this interaction is the degree of knowledge evaluation after the TDP - post DRKE. Here the strategic priorities are set, implemented at the end of the TDP. The adjustment of the strategies is according to the range of knowledge obtained. As an example, using designated degrees, we have the calculation of DRKEj with GdCi of the linguistic vector after the output variable DRKE, also hypothetical: (LOW=0.27; AVERAGE=0.44, HIGH=0.17). To find the numerical DRKE, the defuzzified value of the linguistic variable DRKE is found, on a 0 to 1 scale. Thus, the DRKE shown is 0.7863.

III. CONCLUSIONS AND IMPLICATIONS

The study intends to fill an existing planning gap in the innovation value chain in the perspective of the technology development process - TDP. Thus, a model based on the definition of strategy standards in the high

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complexity spectrum was created, according to the Knowledge Theory. How should the structure of a reference model based on the definition of standard strategies in high-complexity spectrum of TDP be? To verify the model, a set of connected and integrated multi-methods was developed and, to demonstrate its feasibility l, a case study of technology based companies in Brazil was developed trying to look, specifically, the development process of technologies of these companies. The central element of the model is the knowledge construction by the members of the multidisciplinary teams according to the products/technologies development process. This was possible by assessing the degree of knowledge evaluation of the actors in the multidisciplinary teams before and after the development of products/technologies. In other words, from the discrepancies found between the actors' real knowledge (existing) and desired knowledge (actors) to develop products/technologies a set of strategies was proposed to address such discrepancy between real and desired knowledge. Therefore, the construction of knowledge is developed in light of the strategies. This procedure was possible using a hybrid intelligent architecture that combines artificial neural networks and the fuzzy logic. This technology proved suitable to contribute to the robustness of the model and the results achieved. Also, It underscors the importance of the Neurofuzzy Technology acknowledged as an additional managing instrument at the hands of administrators, particularly for the matter at hand, which enabled to identify the Degree of Effectivity of Knowledge Priority Decision in the Innovation Value Chain. This requires a more attentive outlook to questions involving the external environment. Neurofuzzy technology has been applied to support the decision making process in problems that involve subjective and objective attributes. A Neurofuzzy model was structured and the result was designated Degree of Mode Effectiveness, representing the level of adequacy of the mode option to the manager's needs. The results obtained with the application of the proposed model show that this technology is adequate for supporting decision-making, mainly due to its low level of complexity and to its flexibility, which allows the input and output of variables.

Thus, the main objective proposed was to draw attention to the relevance and opportunity to refine efficiency and innovation in planning. Therefore, a reference model was designed for standard strategies in a highly complex spectrum/knowledge network to evaluate the different degrees of knowledge in TDP. With the models and international experiences, the best and worst practices enable to discuss this reference model in a plausible and feasible manner. Of course many questions remain to be further developed in other studies of this nature and we hope to have contributed to a plausible methodological discussion, but which can still be more explored. It is important to understand the TDP in the innovation value chain considering that the needs of the different strata of society are best served when handled collectively and collaboratively.

Considering the various dimensions, the results show that there is no considerable predominance of one or another degree of knowledge, but it is certain that this knowledge is on the agenda and should be marked out as a timely priority, in the context of systemic efforts in order to define and redefine new planning strategies over time. It is plausible that the construction of knowledge takes place over a continuous process and converges to the desired profile, which is constantly changing due to the acquisition of new knowledge. In this way, the policy of product development will be anchored in an instrumented planning in view of the actors of the multidisciplinary teams.

Taking into account the methodological procedures, in this field the technique imposed a sufficiently robust and logical/scientific planning standard. The sophistication of the methodological procedures favored different dimensions required to understand and interpret the rationale behind the technologies development process in the innovation value chain. The model is a valuable conceptual tool. There are many challenges that permeate TDP in the innovation value chain, particularly given the efficient and effective instruments, methods, techniques and methodologies that are useful in planning, and which are subject to the insulated inefficiency by rigid standards that stifle the essence of the innovative and flexible nature that should adapt to TDP. The literature has difficulty when addressing this subject, this planning stage is often devoid of effective and appropriate instruments. But it is also true that making use of "ready-made" has resulted in the managers of product development/technology to indefinitely postpone the process of reorganizing this segment.

The framework proposed requires the development of formal models to better describe and rationalize the evaluation of strategies, based on best practices in innovation, in which mathematical models are not sufficient to describe situations of complex applications. Experience and human intuition are important in decision processes that require high tolerance for ambiguity. Human experience and intuition are important in decision processes that require high tolerance for ambiguity. The proper use of complex decisions in TDP requires applying specifically designed methodologies that are in agreement with the particularities of each product development project. What is strongly assumed is the fact of recognizing the importance of subjectivity in the decision makers' judgment; their values, their objectives, their biases, their culture, their intuition, as well as the influence of the subjective perception and the understanding of the knowledge available. Here the modeling approach presented gains emphasis, the psychometric



methods and artificial intelligence systems such as the fuzzy logic and neural networks, which when combined are valuable tools with great potential and large-scale added value, contributing to the robustness of the model.

It is also recognized that the use of only one method is often seen as a gross simplification, without adequately reflecting the study object. Then, with this proposal, a reliable, valid, legitimate instrument is sought, one that is capable of evaluating strategies in a high complexity spectrum, based on the intended objectives for each Phase, interpreted from the previous phases and towards the model's intended goal.

It is believed that the failed attempts of the traditional product development methods gain way to reinforce the importance of their role, taking a leap towards more innovative and risk-free models. This does not replace the absolute power control of the activities and actions and also does not disregard what has thus far worked, but rather encourages pragmatism to responsibly implement TDP. Moreover, the process of building an innovative product development opens a new attribute for the relationship between the actors of multidisciplinary teams in the innovation value chain in the technology development process. Considering the traditional practices, it should be noted that, somehow, with all its limitations, managers have tried, in their own way, to face the challenges in the product development/technology. It is also true that this is a general discourse on the development of a model, which may sound rhetorical and somewhat inappropriate for an analytical work.

The approach here is not intended to unconditionally replace the allegedly inefficient models, but rather to value them, enriching them with technical, procedural and managerial advantages. However, these results must be evaluated objectively, based on an advantage indicator of an innovative model given the traditional approaches. With regards to procedures, this proposal also aims to draw attention to:

(i) renew the classical model to develop products with creative and sophisticated elements and procedures, which would replace the merely technocratic methods and traditional techniques;

(ii) adopt decision support methods, as shown and demonstrated throughout this model, analysis and evaluation, which are better suited to deal with the complexity and subjectivity of the result impacts;

(iii) a procedure, that is, a set of adjusted procedures, supported by instruments for legitimacy, validity and reliability of the proposal presented.

It is also clear that the list of priorities of the actors' knowledge in the multidisciplinary teams is dynamic, dependent on the existing knowledge and skills essential and desirable in TDP, which emerge during practice, always putting new concepts, new content and demanding new behaviors and technical implementations, which fundamentally requires the ongoing and recurrent reconfiguration that joins the list of new strategies in the knowledge network. Also in this effort, these research priorities of knowledge construction should be permanently and periodically applied. Finally, this study has a solid basis for the continuation of other studies, overcoming unscientific practices that still permeate this object, thus more pragmatic and effective guidelines to subsidize the development of new products in the long term.

Finally, it is important to reinforce that this methodological support does not intend to be complete, but rather as a generator of knowledge elements that are strategic for the development of products. Clearly, it does not intend to be a "straitjacket" methodology, but one that can make a contribution, even through freer paths, which makes the decision spectrum more intelligent, providing essential elements for the development of new products. Moreover, this study was applied to technology based companies in Brazil, and this may represent a limiting factor to this research. It should be considered that this instrument does use not always lead to practical results, since the situations require singularities, differentiating them from similar and apparently comparable situations. The social, cultural, economic, political, and especially technological situations are different. Moreover, these tools cannot be used to predict the future, at most the lessons can help find elements for future scenarios.

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