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ORIGINAL PAPER

Fuzzy decision support for tools selection in the core front end activities of new product development

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Abstract The innovation process may be divided into three main parts: the front end (FE), the new product development (NPD) process, and the commercialization. Every NPD process has a FE in which products and projects are defined. However, companies tend to begin the stages of FE without a clear definition or analysis of the process to go from Opportunity Identification to Concept Generation; as a result, the FE process is often aborted or forced to be restarted. Koen's Model for the FE is composed of five phases. In each of the phases, several tools can be used by designers/managers in order to improve, structure, and organize their work. However, these tools tend to be selected and used in a heuristic manner. Additionally, some tools are more effective during certain phases of the FE than others. Using tools in the FE has a cost to the company, in terms of time, space needed, people involved, etc. Hence, an economic evaluation of the cost of tool usage is critical, and there is furthermore a need to characterize them in terms of their influence on the FE. This paper focuses on decision support for managers/designers in their process of assessing the cost of choosing/using tools in the *core front end* (CFE) activities identified by Koen, namely *Opportunity Identification* and *Opportunity Analysis*. This is achieved by first analyzing the influencing factors (firm context, industry context, macro-environment) along with data collection from managers followed by the automatic construction of fuzzy decision support models (FDSM) of the discovered relationships. The decision support focuses upon the estimated investment needed for the use of tools during the CFE. The generation of FDSMs is carried out automatically using a specialized genetic algorithm, applied to learning data obtained from five experienced managers, working for five different companies. The automatically constructed FDSMs accurately reproduced the managers' estimations using the learning data sets and were very robust when validated with hidden data sets. The developed models can be easily used for quick financial assessments of tools by the person responsible for the early stage of product development within a design team. The type of assessment proposed in this paper would better suit product development teams in companies that are cost-focused and where the trade-offs between what (material), who (staff), and how long (time) to involve in CFE activities can vary a lot and hence largely influence their financial performances later on in the NPD process.

Keywords Decision support · Fuzzy front end · New product development · Fuzzy logic · Genetic algorithms

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Abbreviations

AI	Artificial intelligence
CFE	Core front end
DK	Denmark
DSS	Decision support system
EI	Estimate Investment
FDSM	Fuzzy decision support model
FDSS	Fuzzy decision support system
FECard	Final evaluation card
FE	Front end (fuzzy front end)
GA	Genetic algorithm
IT	Italy
MIS	Management support system
NPD	New product development
RBCGA	Real/Binary-like coded genetic algorithm
SDS	Structured decision system

1 Introduction

The innovation process may be divided into three categories: the fuzzy front end—which we will refer to in this paper as front end (FE) to avoid confusion with fuzzy logic—the new product development (NPD) process, and commercialization (Koen 2004), where one of the influential factors is a concrete management mechanism in the stage of FE (Chang et al. 2008).

Although there is no widely accepted definition of the FE, the definition adopted in this work is the following: the FE is defined by all activities that precede the more formal and well-structured NPD process (Koen et al. 2002). It concerns the stages from *Opportunity Identification* to *Concept Definition* (see Fig. 1), under conditions of high market and/or technological uncertainties, and low availability of valuable information. Regarding the latter aspect, Kim and Wilemon (2002) indicate that the technological, market, and resource fuzziness, as well as the uncertain quality of the ideas in the FE, will be harmful to the more formal stage of product development as it increases the chances for reducing the efficiency of the NPD process and

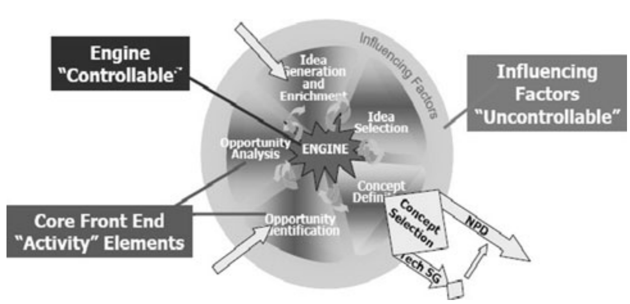


Fig. 1 The new concept development (NCD) model (Koen et al. 2002)

also ending with a non-successful product on the market place (Kim and Wilemon 2002).

Jetter reports that uncertainties concerning the market, technology, environment, and resources are inevitable during the generation of new ideas, and only when the level of uncertainty is below a threshold value, the go/no-go decision can then be finalized {{}}. Finally, Zhang and Doll (2001) reveal that uncertainties arise from customer requirements, competition, and changing technology, and the fuzziness involved in the FE is explained as follows (Zhang and Doll 2001):

(a) Customer: the fuzziness of product portfolio, requirements, demand quantity, and life cycle;
(b) Technology: the fuzziness of supply, specification, and materials;
(c) Competition: the fuzziness of product development and technology adopted by competitors.

Even though there is a continuum between the FE and the NPD, the activities in the FE are often chaotic, unpredictable, and unstructured. In comparison, the NPD process is typically structured, which assumes formalism with a prescribed set of activities and tasks to execute (Koen 2004).

Every NPD process has a FE in which products and projects are defined. However, the ways product ideas are generated, developed, and assessed varies greatly (Koen et al. 2002). The FE is usually described with two approaches: sequential and non-sequential, where sequential frameworks such as Stage-Gate™ model (Cooper 2001) or PACE® (Product and Cycle-time Excellence) (McGrath and Akiyama 1996) model are sometimes considered as inappropriate (Watson and Radciffe 1998). In view of this fact, a need emerges to move from a sequential process model to a non-sequential relationship model (Koen et al. 2002) (see Fig. 1) and with it the need for tools to help structuring and decision-making.

Frequently, companies begin the stages of FE without a clear definition or analysis of the process to go from Opportunity Identification to concepts; often, they either abort the process or start over (Koen et al. 2002). For each stage of Koen's Model, several tools, such as Brainstorming, Mind-mapping, are recommended and can be used by designers and managers to improve, structure, and organize their work in the FE context. In fact, according to the framework proposed by Schilling and Hill (1998), one of the strategic imperatives is using appropriate tools to improve the efficiency of NPD activities (Schilling and Hill 1998). However, these tools tend to be selected and used in a heuristic manner, which has a large influence on the total cost of an NPD project, since 70% of project cost is determined by the decisions made during the FE (Koen et al. 2002) and that cost increases whenever it is necessary to loop-back. Furthermore, some tools are preferred and more effective during specific phases of the FE (European Commission Directorate-General for Enterprise and Industry 2008). Hence, economic evaluation of tools' direct or disposed costs becomes very critical. It is therefore necessary to characterize the tools in terms of their influence on the FE and to estimate the cost of their usage.

This paper focuses on decision support for managers in their process of assessing the cost of choosing/using tools in the core front end "activity" elements (Opportunity Identification and Opportunity Analysis) as shown in Fig. 1. This is achieved by analyzing the influencing factors (firm context, industry context, macro-environment) and then by constructing fuzzy decision support models (FDSM) of the relationships discovered.

The FDSMs will be linking the parameters of tools in terms of explicit costs and persons to the estimated investment of their usage, taking into consideration the use intensity of the tool. The choice of these specific dimensions as the inputs and outputs will be described later in this paper.

The FDSMs generalize and formalize the surveyed managers' qualitative and quantitative assessments. The If–Then fuzzy rules of the FDSMs are explicit and can be used as future decision support rules in the FE, as they could help to improve the understanding of this less structured phase of NPD. Furthermore, the FDSMs enable a company/manager to better understand the management of its cost structure during the CFE activities.

In this research work, the use of a *Fuzzy* decision support system approach is justified by its suitability to be used in situations that are too complex or ill-defined to be reasonably described in a conventional quantitative manner, which is the case for the FE activities. Traditional mathematical approaches do not always effectively tackle such uncertain variables to derive a satisfactory solution. The use of linguistic terms reflects the uncertainty and fuzziness of human evaluation; fuzzy sets theory is suitable to directly apply to such approximate reasoning (Lu et al. 2008). Furthermore, one of the major drawbacks of traditional methods, such as mathematical programming and economic models, is the requirement of large amounts of information, which raises the problems of data reliability and practicability in the FE, where very little information is available (Lin and Chen 2004).

The most common technique used for decision support in industries is expert knowledge and judgment. Human fuzzy reasoning is usually employed to deal with such complexity and uncertainty (Chang et al. 2008). Viewed from this perspective, the development of fuzzy set theory and fuzzy logic, was motivated to a large extent by the need for a computational framework for dealing with humanistic systems, that is, with systems in which human judgment behavior and emotions play a dominant role (Karwowski and Mital 1986; Zadeh 1973).

To sum up, the concept of linguistic variables, defined as variables with values that are not numbers, but words or sentences in natural or artificial language (Karsak 2000), appears as a useful means for providing approximate characterization of phenomena that are too complex or ill-defined to be described in conventional quantitative terms (Zadeh 1975).

The questions to be asked here are "why it is important to adopt a decision support system (DSS) in the FE?" and "how the DSS can affect managers' decision-making processes?"

Rangaswamy and Lilien (1997) define, in their review of software tools for decision support in NPD, two broad non-exclusive categories:

1. Software designed to enhance decision-making associated with NPD: these packages enhance decision-making by enabling managers to use available information more effectively, encouraging the generation and evaluation of more decision options, or improving consistency of decision-making.
2. Software designed to facilitate the process of NPD.

The FDSMs proposed here fall into the first category. Moreover, a better understanding of managerial decision-making and problem-solving has led to a demand for better DSS. A distinction can be made between completely structured decisions and unstructured ones, although in reality there is a continuum with completely structured decisions at one extreme and completely unstructured ones at the other. On the one hand, the process of making a completely structured decision is algorithmic (logical, quantitative, unequivocal, and entirely defined). On the other hand, the process of making an unstructured decision is heuristic (Neumann and Hadass 1980). The latter seems to be the dominant trend in the FE.

In general, decision-making is not an activity performed at a specific time, but a stepwise process (Neumann and Hadass 1980), and it comprises three main phases: intelligence, analysis and design, and selection or choice (Simon 1960).

A management information system (MIS) supports the process of making unstructured or semi-structured decisions by performing part of the process and providing relevant information. The structure of MIS derives from its operational definition. Two types of logical components can be distinguished: structured decision systems (SDS), which make the structured decisions, and DSS, which supports unstructured and semi-structured decisions (Neumann and Hadass 1980).

Furthermore, along with the NPD stage dimensions, there are no artificial intelligence (AI) applications reported for strategic planning, Opportunity Identification, product/service introduction, or life cycle management. It is in these stages of NPD, especially in the front end stages of *Opportunity Identification* and *Opportunity Analysis*, where more research is needed. Thus, AI and DSS applications in new product development can possibly confer competitive advantage to manufacturing companies (Subba Rao et al. 1999).

Evidence in the literature shows three interesting trends. Firstly, some tools can speed up the FE processes and reduce its costs. Secondly, the use of software tools increases the communication and collaboration in the FE, and both are very important to the innovation process, since information diffusion for the whole NPD team and engagement of the organization's collaborators are significant success factors. Thirdly, the quality of decision is improved (Monteiro et al. 2010).

The research presented in this paper combines both AI techniques, in genetic algorithms and fuzzy logic, and human cognitive decision process for constructing fuzzy models for decision support in the CFE activities of the FE. To achieve this, five different companies were used for the data collection.

2 Research aim

The long-term aim of this research is to support new product development managers when adopting a tool to use during the FE of innovation, being that decision makers tend to be executives whose time is both limited and expensive. Although managers may desire more *effective* decision-making, the ability of a DSS to effect more *efficient* decision-making is also important to creating and maintaining managerial support (Meador et al. 1984). For example, the work presented in (McKeen 1983), 32 business applications systems were surveyed, and it was found that greater time and effort spent on FE analysis resulted in less overall system development time, less overall cost, and greater user satisfaction with the delivered system.

Several commercial software packages have been introduced in recent years, but they focus on idea generation and provide only minimal support for idea evaluation (Rangaswamy and Lilien 1997) and none for the tool selection.

The short-term aim of this research is to support both the *tools selection* processes as the proposed FDSMs deal with the CFE activities.

This will be achieved with the automatic generation of FDSMs that can be used for the following:

- a starting point for tool adoption/use
- a better distribution of assets (human potential/money) versus cost of tool usage
- analysis of costs during different phases of FE

The specific research aim is to focus on the decision support regarding the needed Estimate Investment to carry out activities during the CFE of the FE. In order to generate the FDSMs, one has to identify the input and the output parameters in terms of macro-parameters and the micro-parameters that compose them.

3 Research methodology

An explorative research exercise was first carried out, to classify the tools by reviewing literature. From this, 57 existing tools emerged, which were subsequently assessed and considered. It is worth noting that the word "tools" embraces methods, models, systems, frameworks, and techniques. Tools were assessed in terms of:

- Inputs: information, knowledge, procedures;
- Outputs: products, services, procedures, information, knowledge;
- Resources: two macro-parameters have been chosen from the analysis of the literature to describe the resource requirements, and then, each was divided into micro-parameters.

The research work was carried out through surveying five product development managers from five Danish and Italian companies using 57 tools. The data collection was carried out by means of a three-step procedure described in Sect. 5.

Once the data were collected, FDSM were generated automatically, using a specialized genetic algorithm applied on one part of the data (learning set). This step was followed by the validation of the FDSMs by a set of hidden data not used in the learning.

4 Tools used in core front end activities

From the literature review, many tools that are used in the CFE of the FE emerged. In this section, a clustering of these tools will be carried out in order to ease their analysis and assessment. Some of the methods utilized in the Opportunity Identification stage (structured approach) are Customer trend analysis, Road mapping, Technology trend analysis, etc., whereas it is possible to conduct analysis of the same stage in an informal way with tools such as Ad hoc sessions, Investment Analysis (Koen et al. 2002).

In the Opportunity Analysis stage, it is possible to use the same tools as in the Opportunity Identification stage (Koen et al. 2002). This argument strengthens our choice to focus on the CFE as one stage. Table 1 shows a partial example of the tools' clustering for Opportunity Identification phase. Each surveyed manager was sent a copy of the table.

Table 1 Clustering of tools

Stage of the NPD model	Context	Tool	Short description	Refs.
Opportunity identification	Technology trend analysis	S curve	Technology has a life cycle interpreted by a curve that follows an empirical law. It can explain trends about technologies' adoption, improvement, and diffusion	Brown (1992)
	Market research	Standard and dominant design and so on…	and so on …	Schilling (2005)
			…	List (2005)

4.1 Qualitative assessment of tools

In order to identify the dimensions that will define the inputs and outputs of the FDSMs, the authors carried out a qualitative assessment of the tools, in order to identify the requirements of the inputs/resources/outputs of the tools, as shown in Table 2. Once all the tools were characterized, a classification was made, of inputs, outputs, and resources, and with the aim of identifying cluster dimensions (macro- and micro-parameters) that represent the most important characteristics to consider as inputs and outputs for the FDSMs.

From the understanding of inputs and outputs of the tools used in the CFE, it became possible to identify the parameters, giving a better picture of the resource consumption. The clustering of the qualitative data carried out by the authors helped identifying the following macro- and micro-parameters:

- Persons
  - Working hours
  - Training
  - Professional background
- Explicit Costs
  - Things to use
  - Utilities
  - Software/hardware
  - Incentives

In the first macro-parameter *Persons*, "Working hours" refers to the hours dedicated from workers, for example, to

Table 2 Tools characterization

Tool/stage	Inputs	Resources	Outputs
Customer trend analysis			
Category appraisal (segmentation)	Customer-based approach	Persons	Complete definition of each segment
	Product-based approach	Working hours	Profile of each segment (give a name)
	Dependent variables	Time to decide what data will be collected	
	Independent variables	Time to decide how data will be gathered	
	Questionnaire	…	
	Interview	Training	
	Techniques	Professional background	
		Marketing analysts	
		Customer service analysts	
		Explicit costs	
		Things to use	
		Audio recorder (for interview)	
		Utilities	
		Room	
		Software/hardware	
		Software	
		PC	
		Incentives	
		Correlations with firms' results	

select participants in workshops, to collect data, to analyze results.

"Training" refers to the necessary amount of hours to give adequate instructions, information, or knowledge in order to perform a particular role, for example, in the conduction of a brainstorming session.

"Professional background" is a qualitative parameter, but it is possible to transform it into a quantitative parameter by means of simple data manipulation. For instance, comparing the background of the participant to what would be required to use the tool efficiently could be a possible way. A concrete example would be: in order to use tools about category appraisal efficiently, the participant should have marketing analysis background and customer service analysis skills, but they might not have them.

The second macro-parameter is Explicit Costs, where "Things to use" refers to paper, pens, pencils, and audio recorder, which could be needed during the use of a specific tool.

"Utilities" refers to room availability, internet connection, whiteboards, tables, etc., while "Software/hardware" is related to the use of office suite, printers, etc., as support to the decision-making process. Finally, "Incentives" refers to financial incentives to participate and/or adopt a specific tool. In the FDSMs, the macro-parameters are the output of the models, while the micro-parameters are the inputs.

5 Data collection from the managers

In order to collect data from the companies' managers, semi-structured interviews were carried out. Many factors such as available time, factors from inside and outside the work place, the relationship with the interviewer, and the respondent's experience could influence the respondent's answers. It is very difficult for the interviewer to control these parameters; hence, in order to reduce the effect of bias, a three-step methodology was adopted, as described in the next paragraphs and illustrated in Fig. 2.

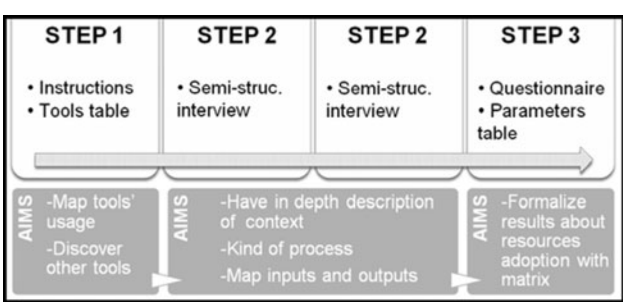


Fig. 2 Three-step data collection approach

5.1 Tools selection by the managers (step 1)

A document containing indications about the context of the FE with a focus on the CFE along with instructions about how to proceed was sent by e-mail to the managers. The managers also received a brief explanation of the context before they accepted to collaborate in the study.

Then, the managers were presented with a table containing all the tools reported by the authors from the literature. This table was used to understand whether the company uses/knows the tool in their CFE activities, and/or whether it was used in combination with other tools. Additionally, the managers could add tools used in their organization if not listed in the provided table. The aim of step 1 was to map the usage of the tools usage within context of practices and processes of the companies and to discover other tools that did not emerge from the literature surveying.

5.2 Mapping inputs and outputs (step 2)

This step is a semi-structured interview that was carried out face-to-face (at the company's office), or via video conference. Regarding the point of time at which the interview takes place, respondents were asked to describe the development of the last new product brought onto the market (last-incident method), followed by more specific questions about key FE parameters, to finally end with questions about the tools. The aim of this step was to get an in-depth description of the environment in which the interviewee operates, to release further comments about step 1, to understand whether the process is structured or not, and to draw a comprehensive mapping of the inputs and outputs of tools. In this step, the macro- and micro-parameters defined above were discussed, understood, and confirmed by the managers.

5.3 Usage intensity and parameters assessment (step 3)

This step was carried out via e-mail, once the tools used by the managers and the macro- and micro-parameters had been defined.

The manager stated the usage intensity of each tool per micro-parameter using a Likert scale 1–5. An example of the tables they received is shown in Table 5.

This was followed by an assessment of the macro-parameters and micro-parameters, with a focus on the rate incidence (%). The aim of this step was to formalize results about the usage of resources implied by adopting a specific tool. Each manager, while considering his budget, had to set a percentage (%) of how much each of the dimensions influences the *Persons* and the *Explicit Costs* dimensions as shown in Table 3 and Table 4. It was necessary that the macro-parameters *Persons* and *Explicit Costs* added up to 100% (Table 5).

Table 3 Persons parameter among its sub-parameters

Persons	
Sub-parameters	%
Working hours	
Training	
Professional background	

Table 4 The percentage of the Explicit Costs parameter among its sub-parameters

Explicit costs	
Sub-parameters	%
Things to use	
Utilities	
Software/hardware	
Incentives	

Once these three steps were finalized by the managers, the results were summarized in a matrix called final evaluation card (FECard), illustrated in Fig. 3. FECard is composed of two axes: the vertical one for indicating the parameters' weights and the horizontal one to represent the use intensity; two grids are constructed to obtain the estimate investment (qualitative evaluation) related to a single tool.

The output obtained for the Estimate Investment for all the tools will be used as an output for either learning or validating the automatically generated FDSMs.

6 Case study and results

Every manager surveyed had at least eight years of experience in product development (experts). This number might seem low for some, but there is no agreement about the sample size and no standards by which a sample size selection could be evaluated to select the number of expert participants required (Lai et al. 2006) to assess the generalization of the results. The number of expert participants is usually far less than the number of general participants. In the studies presented in (Dalkey and Helmer 1963) and in the research by (Strasser et al. 2005), six and seven experts participated, respectively, while only four experts were surveyed in the work presented in (Dore et al. 2007). Furthermore, from a machine-learning point of view, five data points is considered a low number; however, this was combined with a reviewing of 57 tools of which 35 were selected and assessed. We are far from numbers such as those (1,000) proposed in Reich and Barai (1999);

Table 5 Usage intensity card

Tool	Parameter	Sub-parameter	Use intensity				
QFD	Persons	Working hours	①	②	③	④	⑤
		Training	①	②	③	④	⑤
		Professional background	①	②	③	④	⑤
	Explicit costs	Things to use	①	②	③	④	⑤
		Utilities	①	②	③	④	⑤
		Software/Hardware	①	②	③	④	⑤
		Incentives	①	②	③	④	⑤
SWOT analysis	Persons	Working hours	①	②	③	④	⑤
		Training	①	②	③	④	⑤
		Professional background	①	②	③	④	⑤
	Explicit costs	Things to use	①	②	③	④	⑤
		Utilities	①	②	③	④	⑤
		Software/Hardware	①	②	③	④	⑤
		Incentives	①	②	③	④	⑤
Brainstorming	Persons	Working hours	①	②	③	④	⑤
		Training	①	②	③	④	⑤
		Professional background	①	②	③	④	⑤
	Explicit costs	Things to use	①	②	③	④	⑤
		Utilities	①	②	③	④	⑤
		Software/Hardware	①	②	③	④	⑤
		Incentives	①	②	③	④	⑤

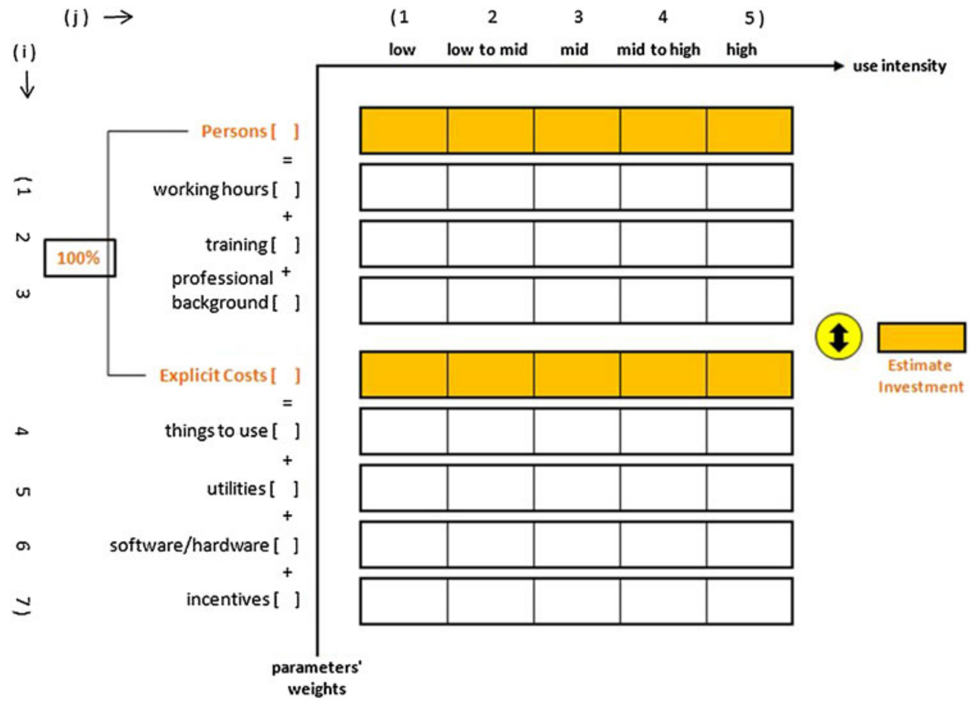


Fig. 3 Final evaluation card

however, in this case, we are dealing with trying to reproduce human assessment in the very specific concept of NPD, where information is considered difficult to collect.

Therefore, five experts used to construct the data sets for automatic learning and validation were deemed to be sufficient for considering the information collected from them of value for modeling the FDSMs. Further details about the surveyed managers and the companies are reported in Table 6.

6.1 Parameter selection for decision support

The three FDSMs developed in this paper are of the MISO (multiple-inputs/single-output) type. Using three MISOs instead of a Multiple Input Multiple Output (MIMO) system has the disadvantage of losing the information that connects the models together; however, it captures better the knowledge encapsulated in each of the macro-parameters. The following sets of inputs/outputs are used:

FDSM1

- Inputs
- Working hours
- Training
- Professional background
- Output
- Persons (investment)

FDSM2

- Inputs
- Things to use
- Utilities
- Software/Hardware
- Incentives
- Output
- Explicit Costs

Table 6 List of companies and managers involved

Company #	Location	Industry	Experience (years)	Representative's role
1	DK	Engineering consultancy	25	Senior engineer and manager
2	IT	Engineering handicraft	8	Export manager
3	IT	Plant protection	13	R&D manager
4	IT	ICT	8	Project engineer manager
5	DK	Healthcare	9	R&D innovation manager

FDSM3

- Inputs
- Persons
- Explicit Costs
- Output
- Estimate Investment

The FDSMs, developed here, are expected to closely match the evaluations of the managers carried out in step 2 of the data collection. This would lead to FDSMs that can be used for decision support by other managers and for other similar tools. Fig. 4 illustrates the schematics of the manager's fuzzy decision support system (FDSS), where the manager starts by typing in a request to the system in terms of observations on the inputs that will provide information on Persons Investments and/or Explicit Costs. Further up the model, an Estimate Investment of the phase can be obtained using the output from the previous two models FDSM1 and FDSM2.

In order to use the FDSS, the manager needs to know approximate levels of cost in terms of hours for *Training* and *Working Hours*, along with building his team for assessing the professional background coefficient; these observations will provide the output *Persons*. Furthermore, the manager needs to assess approximate values in terms of money for the four inputs that provide the *Explicit Costs*. *Persons* and *Explicit Costs* crisp outputs will provide the manager with a general *Estimate Investment* of the usage of the tool in the CFE.

If the manager wants to analyze the incidence rate for both macro-parameters on the *Estimate Investment*, then he can use the FDSS to alter the values of the sub-parameters and see the change in cost. This can be useful to take future specific interventions into consideration to try to improve the performance of CFE activities and resources allocation, or to assess the investment importance in hours and money per level.

6.2 Construction of the learning data sets

In order to increase the generalization value of the models, only data from tools that were used by the majority of the companies are included in the learning of the FDSMs, as the tools used for learning were assessed by at least three out of five managers. This translates into at least three companies have reported using the tool, and at least one of the three companies is situated either in Denmark (DK) or Italy (IT). The tools can either be used in the Opportunity Analysis phase, the Opportunity Identification phase, or both. The tools meeting these constraints are listed in Table 7.

The remaining data from the tools that did not meet the above-mentioned constraints will be used for validation of the automatically generated models.

In order to understand how the data were gathered, we present here an example with one company. In this case, "Company 1" will be used. In order to gather quantitative data, a formalization of results is carried out in terms of

Table 7 Tools meeting the constraints for model construction

Name of the tool	# of managers using the tool	# of countries
Brainstorming (Rossiter and Lilien 1994)	4	2 IT + 2 DK
SWOT analysis (Kotler 1990)	4	2 IT + 2 DK
Mind-mapping (UNIDO 2005)	3	1 IT + 2 DK
Science and technology road mapping (Kostoff and Scaller 2001)	3	2 IT + 1 DK
Corporate or product technology road mapping (Kostoff and Scaller 2001)	3	2 IT + 1 DK
Category appraisal (Myers 1996)	3	2 IT + 1 DK

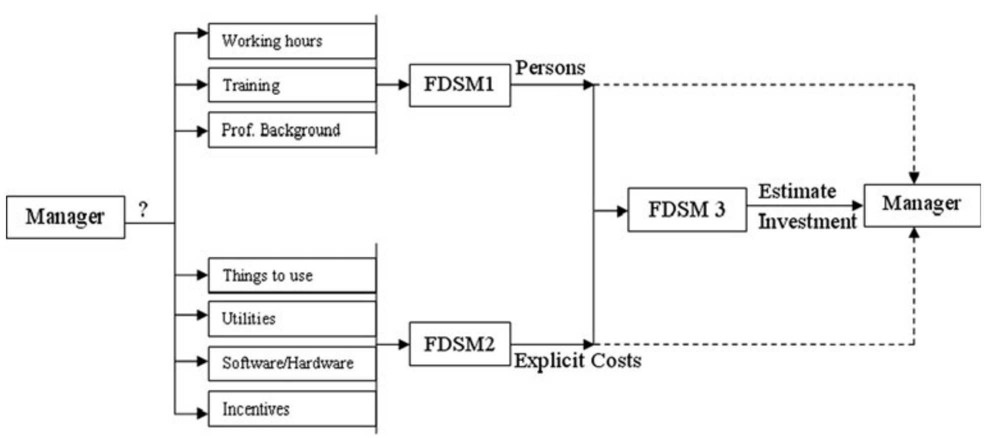


Fig. 4 Schematics of the managers fuzzy DSS

resources requirements per tool. The results can help the company to take into consideration the distribution and allocation of resources, as estimated by the manager (e.g., spotting inefficient allocation of resources). Company 1's Persons and Explicit Costs parameters usage are illustrated in Fig. 5.

The Persons' micro-parameters are expressed in terms of TIME. However, the Explicit Costs' micro-parameters are expressed in terms of MONEY within the company. Considering the budget dedicated to the early stages of the FE, the higher incidence is given by the macro-parameter Persons.

Furthermore, for each tool, the company's manager had to state the intensity of use of the tools based on a Likert scale 1–5, where 1 means low use intensity and 5 means high use intensity. Figure 6 shows an example for the tool Brainstorming.

Finally, the information collection is organized by the mean of the 3rd step, where the data is formalized. The third step aims at formalizing the resource requirements. The formalization is carried out using a matrix FECard, thanks to which it is possible to calculate the Estimate Investment (EI) per tool according to the following formula:

$$\sum_{i=1}^{7} w_i \left(\sum_{j=1}^{k} l_{jk} \right) = l_{\mathrm{EI}} \tag{1}$$

where $i = 1, \ldots, 7$ (micro-parameters in the FEC), $j = 1, \ldots, 5$ (use intensity levels), $k =$ the selected use intensity level in the FEC, $w_i =$ micro-parameters' weights, $l_{jk} =$ resultant use intensity level with the cumulative function, and $l_{\mathrm{EI}} =$ Estimate Investment level.

The cumulative summation was adopted so that the real weight of each level was better represented (instead of linear evolution). From Fig. 7, on the scale showing the low level to high level, in reality the value for low- to mid-cell is 3 and not 2 as shown, the same goes for the mid-cell as it is 6 and not 3, and so on.

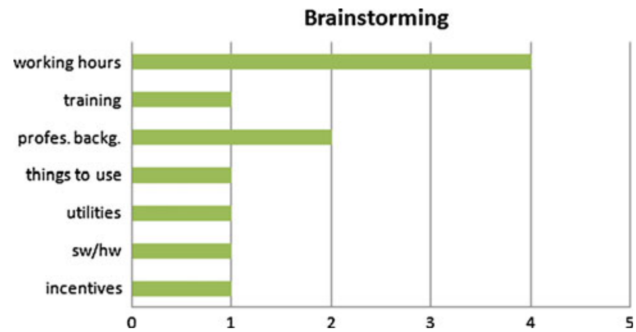


Fig. 6 Company 1's manager use intensity levels for Brainstorming

The values obtained by Eq. 1 are used as the output training value levels for the FDSM3, while the intermediate results are used for FDSM1 and FDSM2 (see Fig. 4). The approach described above was carried out for each company and tool, and used to build up the training set for FDSMs learning.

6.3 Automatic learning and generation of FDSM

The construction of the FDSMs is carried out automatically using a specialized genetic algorithm (GA). GAs are powerful stochastic optimization techniques based on the analogy of the mechanics of biological genetics and imitate the Darwinian *survival of the fittest* approach (Goldberg 1989). Each individual of a population is a potential FDSM, where four basic operations of the Real/Binary-Like Coded GA (RBCGA) learning are performed: reproduction, mutation,

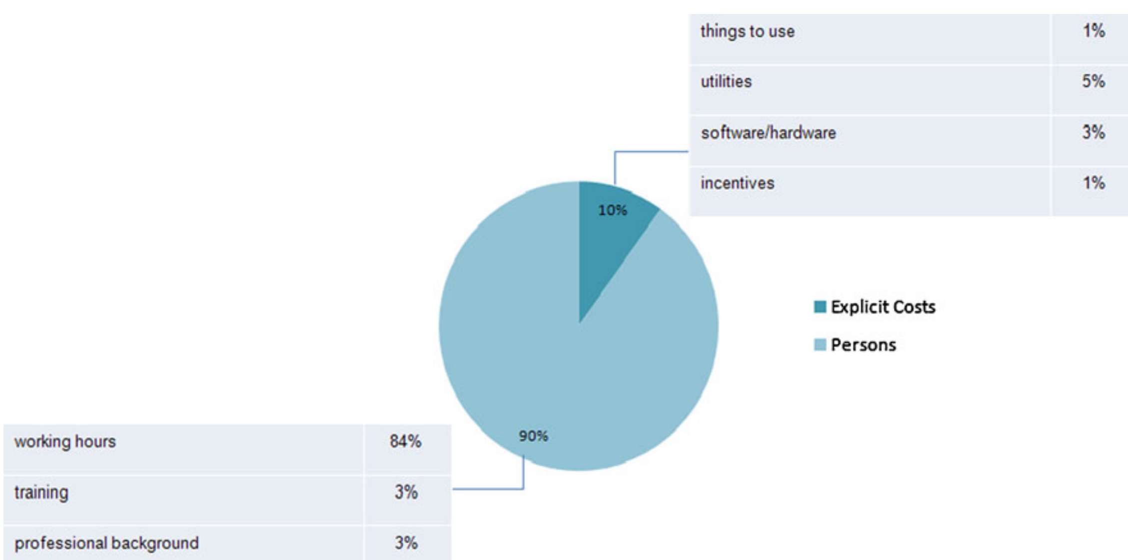


Fig. 5 Incidence rate of explicit costs and persons on the company 1's budget

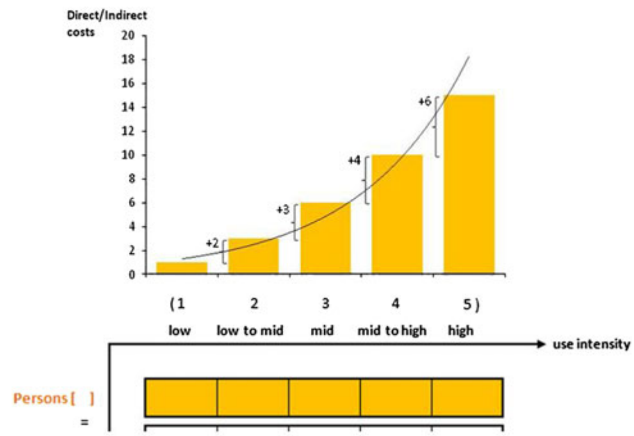


Fig. 7 Tools' costs incidence per level

evaluation, and natural selection. The RBCGA developed by the authors combines a real coded and a binary coded GA. The reproduction mechanisms are a multi-crossover proposed by the authors (Achiche et al. 2004a) and a uniform mutation. More details are given in the following sections.

6.3.1 Coding and evolutionary strategy of the RBCGA

The *genotype* of an FKB is the coding of its parameters into chromosomes. The *genotype RG* corresponds to several independent sets of real numbers and a set of integers.

$$\mathrm{RG} \equiv \{\mathrm{RG}_{\mathrm{sets}}, \mathrm{RG}_{\mathrm{rules}}\} \tag{2}$$

where $\mathrm{RG}_{\mathrm{sets}}$ and $\mathrm{RG}_{\mathrm{rules}}$ are respectively the genotypes of the fuzzy sets and the fuzzy rules. The *genotype* contains the following items:

(A) Input/output premises: A set of real numbers (coordinates of the tip of the triangular fuzzy sets), for the sake of coding simplicity, only non-symmetrical-overlapping triangular fuzzy sets for premises and symmetrical triangular fuzzy sets, were considered for the conclusion. There are as many real number sets as there are premises in the problem, and one set for the conclusion. Each set contains a predefined maximum number of real numbers representing the location of the summit of each fuzzy set on each premise and the conclusion. The two summits located at the minimum and maximum limits of each premise and the conclusion are not coded, since they are constant throughout the evolution.

The genotype of the fuzzy sets of premise i is given as:

$$\mathrm{RG}_{X_i} = \left\{ \underbrace{x_1}_{\mathrm{summit}_1}, \underbrace{x_2}_{\mathrm{summit}_2}, \ldots, \underbrace{x_i}_{\mathrm{summit}_{Ki}} \right\} \tag{3}$$

where K_i is the number of fuzzy sets on the premise i (or the conclusion). The limits of the premises (range) are not included in the sets. RG_{sets} is then given as:

$$\mathrm{RG}_{\mathrm{sets}} = \left\{ \underbrace{\mathrm{RG}_{X1}}_{\mathrm{premise}_1}, \underbrace{\mathrm{RG}_{X_2}}_{\mathrm{premise}_2}, \ldots, \underbrace{\mathrm{RG}_{X_i}}_{\mathrm{premise}_i}, \ldots, \underbrace{\mathrm{RG}_{X_c}}_{\mathrm{conclusion}} \right\} \tag{4}$$

(B) Fuzzy rules: The fuzzy rules were coded as a set of integers representing an ordered list of the combination of the premises. Each integer in the set represented a conclusion fuzzy set summit (Fig. 8). The genotype of the fuzzy rules is given as:

$$\mathrm{RG}_{X_i} = \left\{ \underbrace{r_1}_{\mathrm{rule}_1}, \underbrace{r_2}_{\mathrm{rule}_2}, \ldots, \underbrace{r_k}_{\mathrm{rule}_K} \right\} \tag{5}$$

The initial population of FKBs is composed of P randomly generated FKBs. The *genotype* of each new solution contains all the sets mentioned above. However, as explained below, the size of the sets can decrease. The maximum number of fuzzy rules is computed as:

$$K = (K_1) \times (K_2) \times \cdots \times (K_N) \tag{6}$$

This number is automatically set and varies with the variations of "*Ki.*" Reproduction is performed by *crossover* of the parent's *genotype* to obtain the offspring's *genotype*. The reproduction of the FKBs in the RBCGA is performed through three crossover mechanisms, each one having a certain purpose to achieve, as explained below.

It is worth noting that in this paper, if–then rule statements are used to formulate the conditional statements that comprise fuzzy logic. A single fuzzy if–then rule assumes the form if x is A then y is B, where A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively. The "if" part of the rule "x is A" is called the antecedent or premise, while the "then" part of the rule "y is B" is called the consequent or conclusion.

(A) Multi-crossover

The multi-crossover mechanism is a combination of two crossovers applied on different parts of the *genotype*. These two mechanisms are governed by an initiating probability pr_1 and are described as follows:

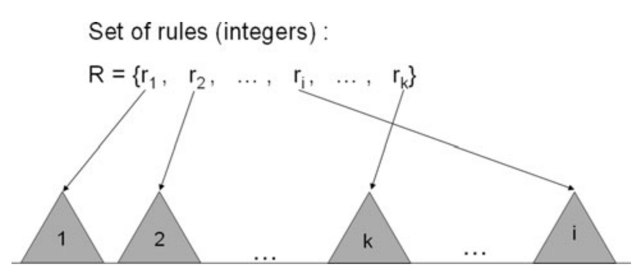


Fig. 8 Reproduction mechanisms

A. Premises/conclusion crossover

The mechanism used is called blending crossover α (BLX-α) (Eshelman and Schaffer 1993), where α determines the exploitation/exploration level of the offspring.

The parameter α is set to 1.0 for the first third of the generations (exploration), to 0.5 for the second third (relaxed exploitation), and finally to 0.1 for the last third of the evolution (exploitation).

(B) Fuzzy rules crossover

Since the part of the genotype representing the fuzzy rule base is composed of integer numbers, the crossover on this part of the genotype is done by simple crossover. The operation is performed by inverting the end part of the sets of the parents at a randomly selected crossover site.

(C) Fuzzy Set Reducer

This mechanism aims to increase the simplicity level of the FKBs by randomly selecting a fuzzy set on a premise and erasing it together with its corresponding fuzzy rules. This mechanism allows one to obtain different and simpler (less information) solutions (i.e., FKBs). This mechanism is governed by the initiating probability pr_2.

(D) Mutation

Mutation is the creation of an individual by altering the gene of an existing one. The probability pr_3 governs the occurrence of this mechanism. The *mutation* used in the RBCGA is a random mutation (uniform), applied to one randomly selected individual (Cordon et al. 2000).

(E) Natural Selection

Natural selection is performed on the population by keeping the "most promising" individuals, based on their fitness. The first generation begins with P FKBs, and the same number is generated by crossover and mutation. To keep the population constant, natural selection on the $2P$ FKBs was applied by ordering them according to the performance criterion and keeping the P first FKBs.

6.3.2 Learning process

The learning process is formulated as an optimization problem applied to the numerical data, using the RBCGA in order to produce near to optimal FKBs. An FKB contains the following entities/information:

1. the number of premises (inputs) and the number of conclusions (outputs);
2. the number of fuzzy sets and their distribution on the premises and the conclusions;
3. the fuzzy rules (fuzzy rule base).

Item 1 is a part of the problem's input data, and all the features in items 2 and 3 are a part of the learning process. The maximal complexity on each premise (i.e., maximal number of fuzzy sets) is fixed at the beginning of the optimization, and therefore, these entities are not a part of the learning process (the maximal complexity can differ from premise to premise). After a few executions, maximal complexity can be readjusted to a higher number if required. The goal of the learning process is to generate FKBs, while maximizing the performance criteria in terms of accuracy (ϕ). Criteria ϕ is defined in the next section.

The optimization problem can be defined as follows:

$$\mathrm{Max}\, f(\phi) \text{ with } \mathrm{G} : \text{Genotype} \tag{7}$$

6.3.3 Performance criterion of the RBCGA

In this paper, the performance criterion is the accuracy level of the FDSMs (approximation error) in reproducing the outputs of the learning data. The approximation error is a combination between the Δ_{RMS}, measured using the RMS error method, and the absolute error, Δ_{ABS}; the next two equations detail these errors.

$$\Delta_{\mathrm{RMS}} = \sqrt{\sum_{i=1}^{N} \frac{(\mathrm{RBCGA_{output}} - \mathrm{data_{output}})^2}{N}} \tag{8}$$

While the absolute error is measured as follows:

$$\Delta_{\mathrm{ABS}} = \sum_{I}^{N} \mathrm{ABS}\left(\frac{\mathrm{RBCGA_{output}} - \mathrm{data_{output}}}{N}\right) \tag{9}$$

where N represents the size of the learning data. The fitness value ϕ is evaluated as a percentage of the output length of the conclusion L, that is,

$$\phi = \left(1 - \frac{\Delta_{\mathrm{RMS}} + \Delta_{\mathrm{ABS}}}{2L}\right) \times 100 \tag{10}$$

6.3.4 Evolutionary strategy

To generate the FDSMs using the RBCGA, one has to set up the maximum complexity allowed, the multi-crossover probability and the mutation probability. In this paper, the maximum complexity is 5 fuzzy sets per input premise and 12 fuzzy sets on the output. However, the RBCGA can reduce those values. The reproduction probabilities are set to 85% multi-crossover, 15% simplification rate, and 5% mutation; more details on these mechanisms are given in (Achiche et al. 2004b). The simplification % is there in order to reduce the complexity of the fuzzy models and increase their generalization level. The population size is set to 200 and the number of generations to 200. Each run was repeated three times to ensure the robustness of the learning process. At the end of the learning the best individual is selected according to the highest ϕ.

6.4 Fuzzy decision support models

The genetically generated FDSM1 and FDSM2 were obtained with a fitness function value of 99%, and the maximum absolute errors were 0.18 and 0.16 for FDSM1 and 2, respectively, in reproducing the estimations of the managers. It is worth noting that data from the evaluation of six tools were used for the learning.

Both FDSM1 and 2 have only two membership functions per premise: High and Low. The choice of a simple database (only two triangular fuzzy sets on each input premise) is motivated by the fact that simpler FDSMs tends to have higher generalization properties, which allows them to be used on a broader range of tools (Achiche et al. 2006; Duda et al. 2001). The outputs consist of seven fuzzy sets, namely Very Little, Small, Low, Moderate, Modest, Considerable, and Very Sizeable. Figures 9 and 10 show FDSM for the Persons and Explicit Costs macro-parameters; the two FDSMs presented here constitute the first two models of the Manager's FDSS, presented in Fig. 4.

The third FDSM (FDSM3) is the global model that takes as inputs the values obtained from the FDSM1 and 2. However, the manager can use FDSM3 individually to assess the Estimate Investment in tools during the CFE activities. FDSM3 contains two fuzzy sets on the inputs *Persons* and *Estimate Cost*, namely *High* and *Low*, while on the output, four fuzzy sets were enough to model the experimental data: *Very Little, Moderate, Considerable, and Very Sizeable*. FDSM3 was generated with an accuracy of 99% while reproducing the experimental data. The maximum absolute error for FDSM3 is 0.26.

One of the advantages of FDSMs is that the manager can both enter crisp observations in order to predict one of the macro-parameters or use fuzzy sets as inputs and hence add uncertainty to the observations and still get a crisp value as an output; furthermore, the FDSMs can deal with inputs

Fig. 9 Persons FDSM (FDSM1)

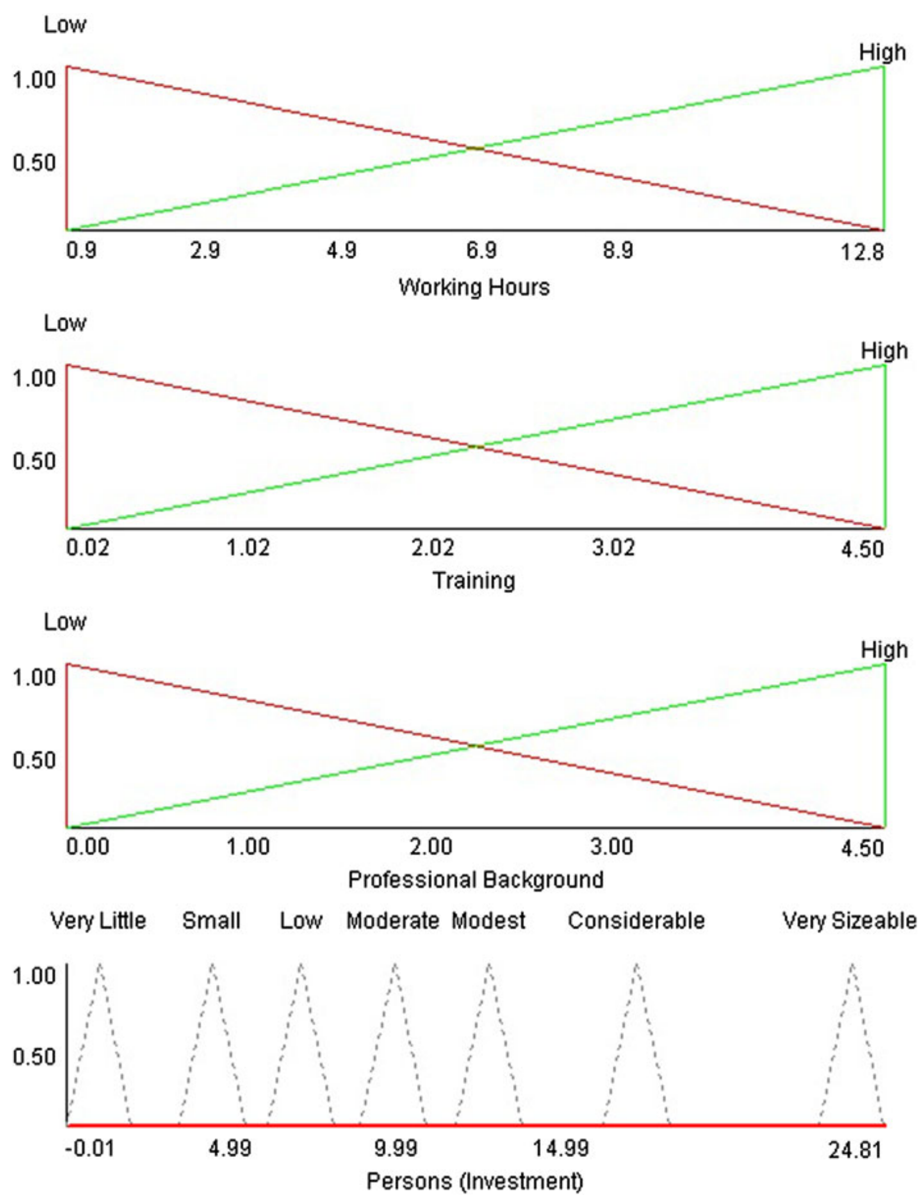
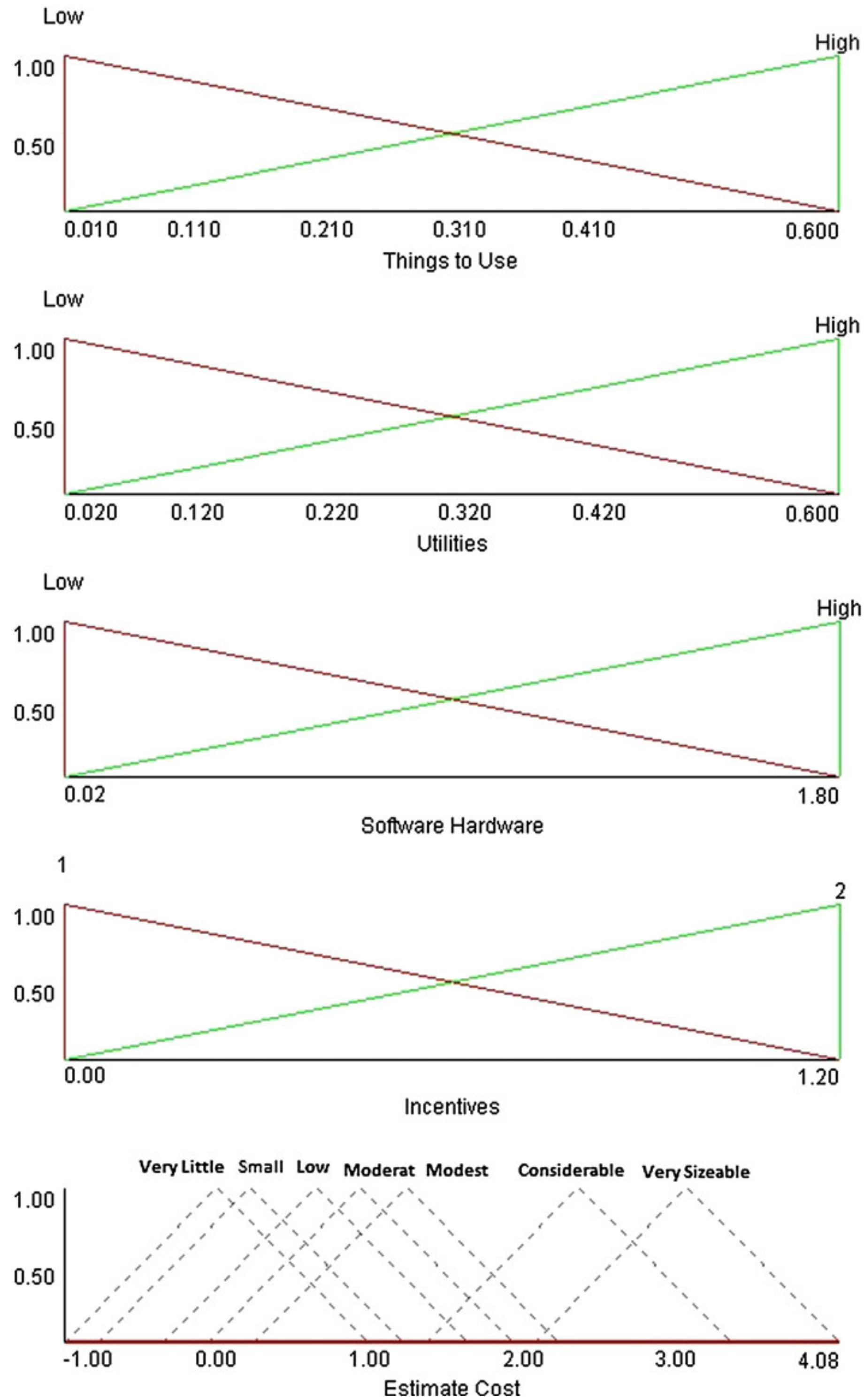


Fig. 10 Explicit costs FDSM (FDSM2)



and outputs of different dimensions; in the case of this paper, there is a mix between hours, money and a non-dimensional coefficients. Figure 11 illustrates FDSM3, which represents the last part of the Manager's FDSS, presented in Fig. 4.

6.5 Fuzzy rule bases

In order to add to the knowledge about relationships that exist between micro- and macro–parameters, the fuzzy rules of the previously generated FDSMs are presented

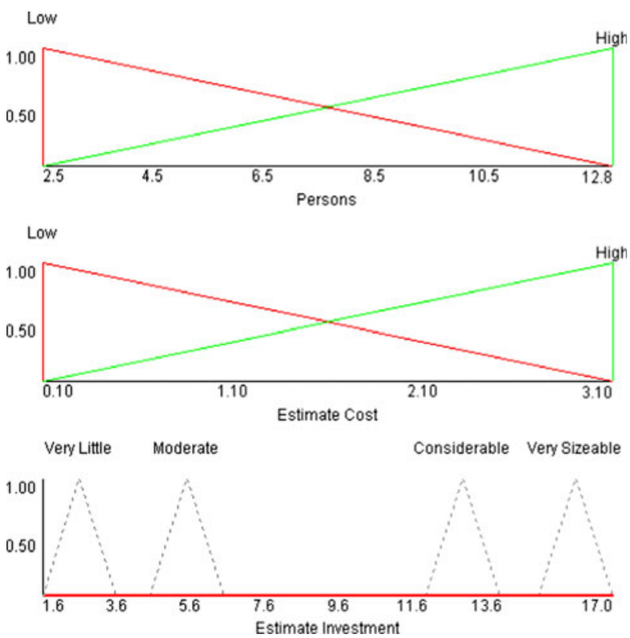


Fig. 11 Estimate Investment FDSM (FDSM3)

Table 8 Fuzzy rules for explicit costs

Things to use	Utilities	Software hardware	Incentives	Estimate cost
Low	Low	Low	Low	Very small
Low	Low	Low	High	Small
Low	Low	High	Low	Low
Low	Low	High	High	Very sizeable
Low	High	Low	Low	Low
Low	High	Low	High	Very sizeable
Low	High	High	Low	Very sizeable
Low	High	High	High	Very sizeable
High	Low	Low	Low	Low
High	Low	Low	High	Modest
High	Low	High	Low	Very little
High	Low	High	High	Very sizeable
High	High	Low	Low	Considerable
High	High	Low	High	Very sizeable
High	High	High	Low	Moderate
High	High	High	High	Very sizeable

here. It is worth noting that when talking about fuzzy rules, we refer to if–then type of rules that are embedded in a FDSS.

Tables 8, 9, and 10 contain the fuzzy rules. These tables could easily be used by the managers as they provide explicit information on the state of the cost depending on the values selected for the inputs.

These sets of fuzzy rules can help the managers acquire more knowledge of how the financial assessment of tools is

Table 9 Fuzzy rules for persons

Working hours	Training	Personal background	Semantics of estimated cost
Low	Low	Low	Very little
Low	Low	High	Small
Low	High	Low	Low
Low	High	High	Moderate
High	Low	Low	Modest
High	Low	High	Considerable
High	High	Low	Moderate
High	High	High	Very sizeable

Table 10 Fuzzy rules for Estimate Investment

Persons	Estimate cost	Estimate Investment
High	High	Very sizeable
High	Low	Moderate
Low	High	Considerable
Low	Low	Very little

carried out in NPD activities. The semantics linked to the FDSMs through the fuzzy sets and rules help to give a more human assessment of the Estimate Investment.

A possible scenario could be the following: A manager needs to decide between two tools that he thinks are possible to use in a CFE activity. “Tool One” would need a high number of the staff to be involved but with a low estimate cost of using it (no need of computers and so on); this would be assessed as a Moderate cost of usage. “Tool Two” would need a low number of staff to be involved but with a high estimate cost, which would translate into a considerable Estimate Investment. The manager can then take the decision to use “Tool One” as it is cheaper to use from an Estimate Investment point of view.

6.6 Validation of the FDSMs using hidden data

The learning of the FDSMs was performed using data from six tools. However, during the case study, several other tools were selected by the managers, but they did not fulfill the generalization constraints and hence were not included in the learning set of FDSMs. Therefore, the data collected from these tools will constitute the hidden data set used to validate FDSM1, 2, and 3.

The hidden data tests the robustness of the developed FDSMs. Table 11 lists all the tools used for constructing the validation data set along with the frequency of their usage (number of companies using them); they add up to 29 tools. According to the work presented in (Reich and Barai 1999), this type of testing would need a much larger data set. However, we point out that we are using more

Table 11 Tools for model validation

Name of the tool	# of companies using the tool	Country
QFD (Yang et al. 2003)	2	1 IT + 1 DK
PFMP (IPU, York Refrigeration, PTC Denmark 2005)	1	0 IT + 1 DK
Ideal concepts (McAloone and Bey 2009)	1	0 IT + 1 DK
Analogical thinking (Dahl and Moreau 2002)	1	0 IT + 1 DK
Morphological analysis (Prokopska 2001)	1	0 IT + 1 DK
TRIZ (Zhang et al. 2004)	2	1 IT + 1 DK
KJ method (United Nations Centre for Regional Development 2001)	1	0 IT + 1 DK
Design for X (Watson and Radciffe 1998)	1	0 IT + 1 DK
Elicitation (van Kleef et al. 2005)	2	2 IT + 0 DK
Alien Interviewing (Kotler 1990)	2	1 IT + 1 DK
Competitive intelligence analysis (Kahaner 1998)	2	1 IT + 1 DK
Porter's five forces (Grundy 2006)	2	1 IT + 1 DK
Blue ocean strategy (Strat. Canvas) (Chan Kim and Mauborgne 2005)	2	1 IT + 1 DK
Scenario planning (Schoemaker 1995)	2	1 IT + 1 DK
Conjoint analysis (Green and Srinivasan 1990)	2	1 IT + 1 DK
IT road mapping (Kostoff and Scaller 2001)	2	1 IT + 1 DK
PPM road mapping(Kostoff and Scaller 2001)	2	1 IT + 1 DK
PEST analysis (Jones 2007)	2	1 IT + 1 DK
Investment Analysis (Anthony et al. 2007)	2	1 IT + 1 DK
AHP (UNIDO 2005)	1	1 IT + 0 DK
Random word (Richardson et al. 2003)	1	0 IT + 1 DK
Brain writing(Kotler 1990) (Rossiter and Lilien 1994)	1	0 IT + 1 DK
Value appropriation methods (Schilling and Hill 1998)	1	0 IT + 1 DK
GE matrix (Kotler 1990)	1	0 IT + 1 DK
BCG matrix (Kotler 1990)	1	0 IT + 1 DK
S curve (Brown 1992)	1	0 IT + 1 DK
Nominal group technique (Sample 1984)	1	0 IT + 1 DK
Lead user technique (Lilien et al. 2002)	1	0 IT + 1 DK
Focus group (Bruseberg and McDonagh-Philp 2002)	2	1 IT + 1 DK

Table 12 Error and correlations between fuzzy and human predictions

	Max absolute error	Mean absolute error	Correlations (%)
FDSM1 persons	0.41	0.10	99
FDSM2 estimate cost	0.42	0.12	99
FDSM3 Estimate Investment	2.78	0.81	96.3

tools to validate than we used for learning. Furthermore, in this type of study, it would be quite difficult collecting such large data sets (either the number of managers or the number of tools).

The absolute error profile and the correlations between fuzzy prediction and human evaluation are presented in Table 12.

One can see from Table 12 that the mean absolute error is still low for the FDSMs predictions, tested with hidden data. FDSM1 and 2 predicted the human decision with 99% correlation, with a maximum absolute error of 0.42 and a mean absolute error of 0.12. FDSM3 performs less accurately with a maximum absolute error of 2.78, on a scale of 15. However, the average absolute error remains quite low with 0.81 and the correlation fairly high with 96.3%.

7 Conclusion

This paper has proposed general dimensions (macro- and micro-parameters) under which the requirements of the inputs and outputs of the tools used in the core front end of innovation can be clustered. These dimensions were later on used to construct the fuzzy decision support system. We have also shown genetically generated fuzzy logic models for decision support for managers, in order to optimize the use of tools during the core front end activities of the FE of innovation. The genetically generated models do not suffer any bias while reproducing the cost estimations. Each of the fuzzy models is a multiple-inputs single-output fuzzy knowledge base.

The obtained results confirm the possibility of estimating the relative costs of the usage of tools to structure the FE of innovation during the core front end activities, by constructing mathematical models from human knowledge.

The three automatically generated fuzzy decision support models developed here matched the managers' evaluations of the investigated dimensions in the learning phase and remained very stable when validated with the hidden data that were not included in the learning set.

When selecting fuzzy decision support models from the final population of the genetically generated solutions, the authors favoured smaller and more simple rule bases because they could be more easily investigated by managers, in order to understand the influence of the inputs on the outputs and hence better manage the cost of a specific phase in relation to the use of a specific support tool.

This fuzzy logic modeling approach can actually help managers to decide on the financial trade-offs of tool usage and therefore make more informed and target-worthy decisions on tool selection for FE processes. It is important to note, however, that it is critical that the manager has a good knowledge of the tools and is fully aware of what is needed to use the various tools, as this provides the input to the models.

The approach adopted in this paper can easily be extended to the other phases of the FE and can be applied both to a single tool and an entire phase.

The limitation with respect to the automatic extraction of fuzzy models for other adjectives is the lack of variety on some of the tools, which makes it impossible to gather data that can be used as an example for the managers to use as observations into the models. It would be possible to make this modeling more accessible to the end user (product development manager) by creating a predefined database of tools and implementing an interactive interface to gather the end user's specific data based on knowledge from the experts.

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References

Achiche S, Baron L, Balazinski M (2004a) Real/binary-like coded versus binary coded genetic algorithms to automatically generate fuzzy knowledge bases: a comparative study. Eng Appl Artif Intell 17(4):313–325

Achiche S, Baron L, Balazinski M (2004b) Scheduling exploration/exploitation levels in genetically-generated fuzzy knowledge bases, Annual Conference of the North American Fuzzy Information Processing Society—NAFIPS 2004, pp 401–406

Achiche S, Wozniak A, Balazinski M, Baron L (2006) Fuzzy rule base influence on genetic-fuzzy reconstruction of CMM 3D triggering probe error characteristics. Annual Meeting of the North-American-Fuzzy-Information-Processing-Society, NAFIPS, pp 85–89

Anthony RN, Hawkins D, Merchant K (2007) Accounting: texts and cases, 12th edn. McGraw-Hill, New York

Brown R (1992) Managing the "S" curves of innovation. J Mark Manag 9(1):61–72

Bruseberg A, McDonagh-Philp D (2002) Focus groups to support the industrial/product designer: A review based on current literature and designers' feedback. Elsevier, Amsterdam

Chan Kim W, Mauborgne R (eds) (2005) Blue ocean strategy: how to create uncontested market space and make competition irrelevant, 1st edn. Harvard Business Press, Boston

Chang H, Wei C, Lin R (2008) A model for selecting product ideas in fuzzy front end. SAGE Publications, Thousand Oaks

Cooper RG (2001) Winning at New Products: Accelerating the Process from Idea to Launch, 3rd edn. Addison-Wesley, Cambridge, MA

Cordon O, Herrera F, Villar P (2000) Analysis and guidelines to obtain a good uniform fuzzy partition granularity for fuzzy rule-based systems using simulated annealing. Int J Approximate Reasoning 25(3):187–215

Dahl DW, Moreau P (2002) The influence and value of analogical thinking during new product ideation. J Mark Res 39(1):47–60

Dalkey N, Helmer O (1963) An experimental application of the Delphi method to the use of experts. Manage Sci 9(3):458–467

Dore R, Pailhes J, Fischer X, Nadeau JP (2007) Identification of sensory variables towards the integration of user requirements into preliminary design. Int J Ind Ergon 37(1):1–11

Duda RO, Hart PE, Stork DG (2001) Pattern Classification, 2nd edn. Wiley-Interscience, Hoboken

Eshelman LJ, Schaffer JD (1993) Real-Coded Genetic Algorithms and Interval-Schemata. Proc Conf Found Genet Algorithms 2:187–202

European Commission Directorate-General for Enterprise and Industry (2008) Insights on Innovation Management in Europe: Tangible Results from IMP³rove. 10. Office for Official Publications of the European Communities, Luxembourg

Goldberg DE (1989) Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley Longman Publishing Co., Inc., Boston, MA

Green PE, Srinivasan V (1990) Conjoint-analysis in marketing - new developments with implications for research and practice. J Mark 54(4):3–19

Grundy T (2006) Rethinking and reinventing Michael Porter's five forces model. Strategic Change 15(5):213–229

Jones KL (2007) PEST or STEP Analysis. http://www.scribd.com/doc/41512146/2b-PEST-or-STEP-Analysis

Kahaner L (1998) Competitive intelligence: how to gather, analyze, and use information to move your business to the top. Touchstone Books, USA

Karsak EE (2000) Fuzzy MCDM procedure for evaluating flexible manufacturing system alternatives. In: Proceedings of the 2000 IEEE Engineering Management Society, 2000. pp 93–98. doi: 10.1109/EMS.2000.872483

Karwowski W, Mital A (1986) Applications of approximate reasoning in risk analysis. Applications of fuzzy set theory in human factors. Elsevier Science, Amsterdam

Kim J, Wilemon D (2002) Focusing the fuzzy front-end in new product development. R&D Manag 32(4):269–279

Koen PA (2004) The fuzzy front end for incremental, platform, and breakthrough products. In: Kahn KB (ed) The PDMA handbook of new product development, 2nd edn. Wiley, Hoboken

Koen PA, Ajamian GM, Boyce S, Clamen A, Fisher E, Fountoulakis S, Johnson A, Puri P, Seibert R (2002) Fuzzy front end: effective methods, tools, and techniques. In: Belliveau P, Griffin A, Somermeyer S (eds) PDMA ToolBook for New Product Development. Wiley, New York

Kostoff RN, Scaller RR (2001) Science and technology roadmaps. IEEE Trans Eng Manage 48(2):132–143

Kotler P (1990) Marketing management: analysis, planning, implementation, and control, 7th edn. Prentice Hall, New Jersey

Lai HH, Lin YC, Yeh CH, Wei CH (2006) User-oriented design for the optimal combination on product design. Int J Prod Econ 100(2):253–267

Lilien GL, Morrison PD, Searls K, Sonnack M, von Hippel E (2002) Performance assessment of the lead user idea-generation process for new product development. Manage Sci 48(8):1042–1059

Lin CT, Chen CT (2004) A fuzzy-logic-based approach for new product Go/NoGo decision at the front end. IEEE Transactions on Systems Man and Cybernetics Part A-Systems and Humans 34(1):132–142

List D (2005) Market research methods for innovation development: an overview. http://www.unisa.edu.au/cid/publications/methods/npdresearch.pdf

Lu J, Zhu YJ, Zeng XY, Koehl L, Ma J, Zhang GQ (2008) A fuzzy decision support system for garment new product development. In: W Wobcke and M Zhang (eds) Al 2008: advances in artificial intelligence. Lecture Notes in Computer Science. Springer, Berlin/Heidelberg

McAloone TC, Bey N (2009) Environmental improvement through product development: A guide. Danish Environmental Protection Agency, Copenhagen

McGrath ME, Akiyama CL (1996) PACE: an integrated process for product and cycle-time excellence. In: McGrath ME (ed) Setting the PACE in Product Development (Revised Edition). Butterworth-Heinemann, Boston, pp 17–30

McKeen JD (1983) Successful development strategies for business application systems. Manag Inf Syst Q 7(3):47–65

Meador CL, Guyote MJ, Keen PGW (1984) Setting priorities for DSS development. Management Information Systems Quarterly 8(2):117–129

Monteiro C, Arcoverde DF, Da Silva FQB, Ferreira HS (2010) Software support for the fuzzy front end stage of the innovation process: A systematic literature review. 5th IEEE International Conference on Management of Innovation and Technology, ICMIT2010, pp 426–431

Myers JH (1996) Segmentation positioning strategic marketing decisions. McGraw-Hill Inc., USA

Neumann S, Hadass M (1980) DSS and strategic decisions. California Management Review 22(2):77–84

Prokopska A (2001) Application morphological analysis methodology architectural design. Acta Polytechnica 41(1):46–54

Rangaswamy A, Lilien GL (1997) Software tools for new product development. J Mark Res 34(1):177–184

Reich Y, Barai SV (1999) Evaluating machine learning models for engineering problems. Artif Intell Eng 13(3):257–272

Richardson AJ, Hupp RC, Seethaler RK (2003) The use of lateral thinking in finding creative conflict resolutions, 5th Annual Conference of the The American Bar Association Section of Dispute Resolution 2003

Rossiter JR, Lilien GL (1994) New “Brainstorming” Principles. Australian Journal of Management 19(1):61–72

Sample JA (1984) Nominal Group Technique: an alternative to brainstorming. J Ext 22(2). http://www.joe.org/joe/1984march/iw2.php

Schilling M (2005) Strategic management of technological innovation, 2nd edn. McGraw-Hill, New York

Schilling MA, Hill CWL (1998) Managing the new product development process: strategic imperatives. Acad Manag Executive (1993–2005) 12(3):67–81

Schoemaker PJH (1995) Scenario planning: a tool for strategic thinking: Sloan management review. Long Range Plan 28(3):25–40

Simon HA (1960) The new science of management decisions. Harper and Row, New-York

Strasser S, London L, Kortenbout E (2005) Developing a competence framework and evaluation tool for primary care nursing in South Africa. Educ Health 18(2):133–144

Subba Rao S, Nahm A, Shi Z, Deng X, Syamil A (1999) Artificial intelligence and expert systems applications in new product development—a survey. J Intell Manuf 10(3):231–244

UNIDO (2005) Organization and methods. Technology foresight manual. United Nations Industrial Development Organization, Vienna, pp 1–260

United Nations Centre for Regional Development (2001) KJ method, second thematic training course. United Nations Centre for Regional Development, Nagoya, Japan

van Kleef E, van Trijp HCM, Luning P (2005) Consumer research in the early stages of new product development: a critical review of methods and techniques. Food Qual Prefer 16(3):181–201

Watson B, Radciffe D (1998) Structuring design for X tool use for improved utilization. J Eng Des 9(3):211–223

Yang CL, Fang HH, Yang CL, Fang HH (2003) Integrating fuzzy logic into quality function deployment for product positioning. J Chin Inst Ind Eng 20(3):275–281

IPU, York Refrigeration, PTC Denmark (2005) Lean product structures—case: York. Denmark. http://www.ipu.dk/upload/produktudvikling/artikler/leaflet_-_york_-_001.pdf

Zadeh LA (1973) Outline of a new approach to the analysis of complex systems and decision processes. IEEE Trans Syst man Cybern SMC 3(1):28–44

Zadeh LA (1975) The concept of a linguistic variable and its application to approximate reasoning—II. Inf Sci 8(4):301–357

Zhang Q, Doll WJ (2001) The fuzzy front end and success of new product development: a causal model. Eur J Innov Manag 4(2):95–112

Zhang FY, Xu YS, Hu DJ (2004) The objectives decision making study in product innovation development process based on TRIZ technology evolution theory. Mater Sci Forum 471–472:613–619