An evolving fuzzy inference system for extraction of rule set for planning a product–service strategy

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1 Introduction

At least for a decade now, product margins are not the primary yardstick for launching a product anymore, as the profitability of services towards the customer should be also taken into account [1]. One such example is buying a train, where the acquisition costs represent merely 10 % of all costs associated along its life cycle phase, while the other 90 % of costs represent services such as locomotive services, train operations etc. [1]. Another possibility could be simply that a product is completely commoditized and services have to be added on top so that the manufacturer regains its competitive edge; for instance the manufactur-ing enterprise of dynamite ICI-Nobel had to start selling the services of blasting rocks using its product, because dynamite became completely commoditized in the 1990s [2]. This successful and pervasive trend of service bundling with products is referred to as product–services (P–S).

Providing services downstream requires many diverse competences and resources, because the logic and underlying principals differ from the one needed to provide a product. As it is impossible for manufacturing enterprises to own all of them and as the move downstream the value chain requires close collaboration with other enterprises, new form of collaboration arose, like the manufacturing service ecosystem (MSE). It enables a high number of

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enterprises to jointly ideate, compose and provision P–S onto the market in a distributed, dynamic and often non-hierarchical manner. Yet before composing and provisioning them to the market, functional managers in manufacturing enterprises have to define a P–S strategy from the operations management perspective, which represents the nexus of the offering's success. Namely, if the strategy is ineffective, there is a strong possibility that it will be completely rejected by the market. Hence, designing a P–S strategy can be a complex matter, as it is a process of multiple strata, requiring dexterous and experienced managers in the fields of product and service positioning. Further on, strategy definition is based on fuzzy input values, often without clear delineation among each other, where those values and their interpretation cannot be adequately expressed through a binary logic, giving often wobble results. Hence, managers need the ability to assay P–S strategy definition in a systemic manner. Consequently, the *aim* of this article is to undergird the development of an effective decision support system (DSS) for the planning of a P–S strategy within a MSE. Hence, the *objectives* of this article are three; firstly by means of a logical data model, the context of a P–S strategy within a MSE is conceptualized, including the interrelations among the elements within the concept. Secondly, setting clear limits and definitions, the actual business intelligence (BI) sets of rules that are needed by a manufacturer to plan a dedicated P–S strategy within a MSE are designed. Thirdly, to use for the first time an evolving hybrid deci-sion support technique previously proposed from one of the authors [3] adequately modified for matching the context of this application. As the input data needed to design a strategy are often intangible, without a clear delineation among classes (e.g. "Market_1 is more competitive than Market_2"), with more than just binary values that can also overlap among each other and expressed using human language, fuzzy based inference system is used to build the business intelligence data base, which also represents the quintessence of this article. Thus, the locus of this contribution is in the design of a knowledge base for P–S strategy definition with its own sets of fuzzy based rules and the actual evolving hybrid inference system as a base for building a robust DSS for managers in complex systems (e.g. market environments). Those rules extracted by this preliminary version of DSS are introduced in this article to support effectively managers of manufacturing enterprises collaborating within a MSE. Namely, it will enable managers to lean on expert knowledge from the field of P–S, thus having the possibility to increase the speed, reliability and quality of their decisions, as also to decrease substantially their learning time in P–S strategy definition. Hence, the fuzzy based BI sets of rules will support developers of DSS in providing the support of the following three critical performance questions of the P–S strategy definition:

a. *What are the optimal combinations among the Service operations competitive priorities (cost leadership, service differentiation* etc.*) to be combined into a P–S strategy (e.g. after-sales provide, outsourcing partners)?*
   The answer provides an information if the P–S strategy is internally aligned among the possible competitive priorities and thus not relying mostly on the famous "rule of thumb" or solely the "learning by doing technique".
b. *Are the assets, intangible and tangible, that are needed to compose and provision the targeted P–S according to its chosen competitive priorities available within the MSE?*
   The answer provides information, if the manufacturing enterprises within the MSE can compose and provision effectively and efficiently the planned P–S. This tackles especially the issue of feasibility and efficiency.
c. *Does the targeted P–S strategy fit the market's (environment) requirements?*
   The question enables to investigate if the P–S is optimally positioned on the market and gives an opportunity to optimize the strategy accordingly. Hence, this information enables to optimally adjust the external fit between the strategy and the market. Namely, a high external fit improves the overall performance of a P–S oriented enterprise and acts as a predictor for performance [4]. Secondly, after the P–S on the market, managers should perform periodically checks of this fit to see if any adjustment in the strategy or even of the market is necessary.

By converging on one side the abilities of managers and on the other side the BI information system based on knowledge expert in product and service operations, decisions that are more reliable can be made within the MSE enabling to optimally position their new P–S on the market. This BI concept based on fuzzy logic enables to bring strategic positioning one step closer to automated decision making, which is essential to the industry. By decision-making in a fuzzy environment it is meant a decision process in which the goals and/or the constraints are fuzzy in nature, constituting classes of alternatives whose boundaries are not sharply defined [5]. Thus most dimensions related to P–S strategy are not limited to two binary values (0, 1), but usually range somewhere in the middle and are overlapping. Thus, the "truth" of any statements becomes a matter of degree [6].

In order to achieve the article's objectives a BI application framework is first designed. Then, in order to obtain a common understanding and depict the knowledge needed in the targeted decision-making processes, a Logical Data Model for planning a P–S strategy is mapped. Afterwards, the knowledge base and fuzzy rules sets are defined, as part of the fuzzy inference system. At this point, the main phases that represent the locus of this article are graphically depicted and developed. The article concludes with a discussion and promising path for future research.

2 Relation to existing work

2.1 Business intelligence

As the creation of an innovative P–S within a MSE is strongly correlated with making the "right" or at least most optimal decision (e.g. which idea to choose, with which partner to collaborate, what kind of customer segments to attract), managers in Manufacturing Service Ecosystem should and could be supported by BI techniques, as their aim is to support such kind of strategic decision making. BI is a concept of applying a set of technologies to convert data into meaningful information, into knowledge. BI tools include information retrieval, data mining, statistical analysis, and data visualization [7]. According to Petrini and Pozzebon [8] BI shares two basic ideas: (a) the gath-ering, analysis, and distribution of information, and (b) to support the strategic decision-making process. By strategic decisions, it is meant decisions related to implementation and evaluation of organizational vision, mission, goals and objectives, which are supposed to have medium- to long term impacts on the organization, as opposed to operational decisions, which are day-to-day in nature and more related to execution. BI is a very vast area, serving as a conjunction among many techniques and fields. One of the aims of using BI techniques is to support the decision making [9]. In order to exemplify the potential value and applicability derived by applying BI techniques the following examples from a company applying BI tools can be derived [10], such as on assessing the quality of management and collaborations of a company and reviewing its potential. Based on user-friendly but powerful functions, the BI system can retrieve meaningful insights while hiding the underlying complexity of data interpretation. Otherwise BI can be also defined as the process of gathering correct information in the correct format at the correct time; and delivering the results for decision-making purposes, or having a positive impact on business operations, tactics, and strategy in enterprises [11]. From a decision support point of view, which is also the focus of this article, BI is commonly used to support decisions based on a huge amount of data, where extraction techniques are then applied. However, to make a managerial decision complex, the data set does not need to be enormous. The complexity can also arise from at least two sources: (a) the type of data, which is fuzzy and hard to grasp and calculate with (e.g. more price sensitive than "X"), (b) the optimal combinations of data in regards to the inferred conditions. The former demands from managers to master all the variables induced into the decision making process, which is not always the case, especially with the integrations of services with products. Those two factors pose a barrier for reliable (not mostly based on the "rule of the thumb" or "learning by doing") decision-making process on repetitive basis with dynamic constraints inferred form a fast changing environment. Hence, BI is applied also to DSS, which are knowledge-based systems that support decision-making activities above the operational level [12–14]. DSS is a collection of people, procedures, data, and models used to support specific business decision-making tasks [11]. It represents only one category of the information system in the enterprise's computing environment, among which also can be found transaction processing systems, management information systems and enterprise resource planning [15].

2.2 Fuzzy logic

The overarching objective of BI is to provide the right knowledge to the right people at the right time, where "What-if" scenarios and simulation functionality provide advanced, tailored decision-making support [16]. Also it may be argued that the main distinction between human intelligence and machine intelligence lies in the ability of humans to manipulate fuzzy concepts and respond to fuzzy instructions [5]. Thus, if inference is supported by classical "if–then" clauses, this present at least two weaknesses when using it as a mean for supporting decision-making. Firstly, the borders of the raw data are often not sharply delineated and can be expressed using linguistic variables that are closer to our human reasoning, using terms like "tall", "fast", "hot", "somewhat" etc. Although that such reasoning is much more understandable to us, it provides also a new palette of challenges. For instance in sharp contrast to the notion of a class or a set in mathematics, most of the classes in the real world do not have crisp boundaries that separate those objects which belong to a class from those that do not [5]. Namely, fuzzy rule bases have the desirable characteristic of being intelligible, as they are expressed in a language typically used by human experts to express their knowledge [17]. Fuzzy goals and fuzzy constraints can be defined precisely as fuzzy sets in the space of alternatives. A fuzzy decision, then, may be viewed as an intersection of the given goals and constraints. A maximizing decision is defined as a point in the space of alternatives at which the membership function of a fuzzy decision attains its maximum value [5]. Furthermore, fuzzy logic is based among other on approximate reasoning [18–22], as also with an emphasis on linguistic variables [23–27]. Hence, fuzzy technology as a basis of automated software solutions gives a competitive edge for the following reasons [28]: (a) decision systems using fuzzy logic represent experience of experts adequately—fuzzy logic is flexible (it is easy to layer on more functionality without starting again from scratch); (b) like a human expert all aspects of decision making can be integrated into a decision system using fuzzy rules; (c) decision systems using fuzzy logic are easier and more cost-effectively to maintain; (d) as fuzzy logic systems require much less rules than conventional rule based systems the impact of possible changes can be anticipated much easier; (e) fuzzy logic helps minimize false-positives—the concept of fuzzy logic represents fuzzy bounds—thus, the usage of hard bounds which typically result in false-positives is obsolete; (f) decision systems using fuzzy logic are more reliable—conventional rule bases systems have to consider a lot of special cases.

The fuzzy logic has already been used to solve a wide range of issues in enterprises at different fields and at different levels. It has been applied to support the market-entry decision making process [29], in the field of manufacturing [30, 31]. The reader can find the application of fuzzy logic in manufacturing in Azadegan et al. [32], which encompasses and classifies with great clearness the application through different subfields. In the field of strategic planning multiple application have been performed [33–36]. For example some are ranging from performing fuzzy real options valuation, as also in another case developing a fuzzy approach to reducing the so called Bullwhip effect [37], passing by the application of fuzzy logic in financial analysis [38–40]. Fuzzy logic has also been applied in the strategic management of logistics service [41] from an operations management point of view or strategic one [42]. Also one article deals with the field of strategic management [43]. Furthermore fuzzy logic has not been used only on the enterprise level, but also on the supply chain level, as for instance the supplier selection [44–47]. It has been also applied in the marketing field, like market segmentation [48, 49], or used to evaluate perceived service quality [50, 51]. For a more detailed review of the application of fuzzy logic, the reader can turn to Wong and Lai [52] that gives a comprehensible and detailed overview of the application in production and operations management from the year 1998 till 2009. The range of authors applying fuzzy logic for improving the results of decision-making is extremely wide. This pervasiveness only proves that fuzzy logic brings value to supporting the decision support process and it is a mean with high exploitation potential. According to Shapiro [53] the fuzzy inference system (FIS) is a popular methodology for implementing fuzzy logic, which are also known as fuzzy rule-based systems, fuzzy expert systems, fuzzy models, fuzzy associative memories (FAM), or fuzzy logic controllers when used as controllers [54]. The FIS can be envisioned as involving a knowledge base and a processing stage [53]. The knowledge base provides also fuzzy rules needed for the process. In the processing stage, numerical crisp variables are the input of the system. These variables are passed through a fuzzification stage where they are transformed to linguistic variables, which become the fuzzy input for the inference engine. This fuzzy input is the output generated by the rules of the inference engine to fuzzy output. These linguistic results are then hanged by a defuzzification stage into numerical values that become the output of the system.

The use of fuzzy logic is thus necessary in the case of strategy definition, because the premises are expressed as propositions in a natural language, which is the basis for fuzzy logic and computing with words [55]. In a fuzzy environment, the decisional framework differs itself from classical decision making steps, as it features a symmetry with respect to goals and constraints, which erases the differences between them and makes it possible to relate in a relatively simple way the concept of a decision. Namely, in this way the DSS can give reliable and high quality results to managers of manufacturing enterprises planning a P–S strategy within a MSE.

2.3 Product–services and manufacturing service ecosystem

BI intelligence DSS based on a fuzzy inference system is applied onto the decision making process of planning a P–S strategy. This decision process is being undertaken among multiple manufacturing enterprises collaborating within the MSE. Thus, in addition to the field of P–S, the MSE is briefly depicted in this section. P–S in manufacturing appears under many different names, depending on the perspective and focus. Nonetheless there are two main streams, where one is servitization, which is defined as "market packages or bundles of customer-focused combinations of goods, services, support, self-service and knowledge" [56]. Whereas the other one is called product–service system that consists of a mix of tangible products and intangible services designed and combined so that they jointly are capable of fulfilling final customer needs; it is focused also on enhancing sustainability in parallel with the enterprise's competitiveness [57]. Otherwise, Baines et al. [58] has proposed a solution that servitization is the highest level concept, while the concept of product–service system is one of the perspectives. Other perspectives on P–S are also servicizing [59], functional sales [60] or even full-service contracts [61] etc. From an industrial perspective, the concept of product service systems has a big potential, even if it is not so easy to realise for SMEs, due to the fact of much more complexity in the model and the need of a totally new organisation [62]. When manufacturing enterprises are planning and provisioning services, they have to decide upon the following most common operational factors related to service provisioning [63]: equipment/people focus [64, 65], length of customer contact time [66, 67], extent of customization [68–70], the extent to which customer contact personnel exercise judgement in meeting individual needs [71], source of value added, front office or back office [72], product/process focus [68].

Consequently, due to many challenges related to P–S composition and provisioning, a much wider palette of expert knowledge in the field of products as also services is required. In order to make the process of ideation, composition and provision more efficient, manufacturing enterprises are pervasively collaborating among each other in an ecosystem defined as distributed network of people, organisations and machines [73]. Though, as it is mainly made of manufacturing enterprises joining together to design services around their products, the ecosystem is called a Manufacturing Service Ecosystem (MSE), which is semi-formalized and non-hierarchical. In this MSE manufacturing enterprises are foremost sharing their knowledge, as its exploitation can increase their competitive advantage [74]. This knowledge is represented as information about the core assets of each MSE partner. Those assets can be tangible or intangible. Tangible assets in manufacturing can be for instance machines, spare parts etc., while intangible assets represent among others competences, skills, intellectual property, blueprints, software, software code, processes, relations with customers or among enterprises etc. Intangible assets have been also introduced into strategic management, asserting that they are the key drivers whose essence is an idea or knowledge and whose nature can be defined and recorded in some way [75]. Moreover, intangible and tangible assets in a MSE support Knowledge Communities that focus on the facilitation of sharing among a large number of participants having a shared concern (purpose-driven) [76]. As the transition from products to services is expected to be difficult to realize [77], information about the correct P–S strategy are essential. Nonetheless renown authors have already provided guidelines, among others, to managers by means of frameworks for choosing and defining a P–S strategy; for instance Tukker [57] and Baines [78]. Otherwise, when a company emphasizes two or more competitive priorities an unaided manager faces a complex decision problem in choosing from alternatives [79]. Hence, ICT solution should support their decisions.

As many articles focus on the P–S development part and on the actual transition, this article focuses on one step before, the planning phase. Thus, this article proposes to design a rule set that can be integrated into a DSS for planning a P–S strategy to help managers make more accurate decisions. This means to help them optimize the alignment of competitive priorities in order to form an effective P–S strategy, secondly to scrutinize the feasibility of such strategy by identifying the needed assets within the ME. Thirdly to validate this P–S strategy against the market requirements, being the external fit [80]. The concept of fit is based on the assumption that an organization's ability to achieve its goals is a function of the congruence between components/variables [81].

3 Methodology

The fuzzy based DSS is a mean for providing managers BI benefits. In this article the DSS is encompassed within the process of applying BI. The process described is partially based on the one presented by Zeng et al. [11], although with some distinctions: like the integration of the FIS and the adding of additional interactive processes. The process has the following main steps: (1st) problem description, (2nd) Logical Data Model for P–S strategy planning, (3rd) data pre-processing, (4th) application of the FIS, (5th) interpretation and evaluation of results and (6th) acting on results. This article encompasses from step one till including the fifth step. In the continuation, those steps are scrutinized in details, though focusing on the second, third and fourth step including the intermediate step of—learning.

This process of BI application will serve also as the main framework to guide the reader through the model conceptualization and application.

In the first step, the problem and reasoning for using BI will be elucidated and positioned into the context. Thus how can manufacturing enterprises benefit from BI while planning, positioning and provisioning a P–S within a MSE. The second step will be clarifying the relations between the previously identified business issues and the data related to them, depicting to the reader the main interrelations. The third step Data pre-processing will be briefly presented. In the fourth step the knowledge base and the sets of fuzzy rules will be defined. As the quintessence of this DSS lies in the source of its knowledge base, the article integrates established service operations management principles that have been detailed and validated through empirical application on a set of manufacturing enterprises [4]. The purpose of Gebauer's study was to identify service strategies that correspond with specific environment–strategy fits. He used an exploratory factor and cluster analysis for testing Western European enterprises for a fit between their service oriented strategies with the environment. He identified four most common combinations of competitive priorities, four types of environments, as also four optimal P–S strategies that fit the environment. This robust data set will be used as an essential part of this knowledge expert database. In the next step a synthetic data base was designed and populated, performing the actual inference system. Finally, the data base was also tested using EFuNN/ENFiS method, thus the evaluation of the acceptability of the model in terms of robustness and applicability in real environment [11] is performed.

In the next section, the BI information system for decision support is designed. It follows the steps arising the BI application procedure (Fig. 1). The aim of this section is to give a contextual framework for the fuzzy based DSS, to design the knowledge base and the fuzzy rules, which can be used by the BI information system.

4 Fuzzy based rule set development for P–S strategy planning

4.1 Context: challenges and proposed solution

In this step the main business problem is described, from which the added value of BI is visible. One possibility how manufacturing enterprises can increase and sustain their competitive advantage is by planning and provisioning collaboratively, within a MSE, numerous P–S. The managers before launching such new P–S should go through the following steps that are partially based on Lowson [82]:

a. planning:

- defining the competitive priorities of a service operations strategy;

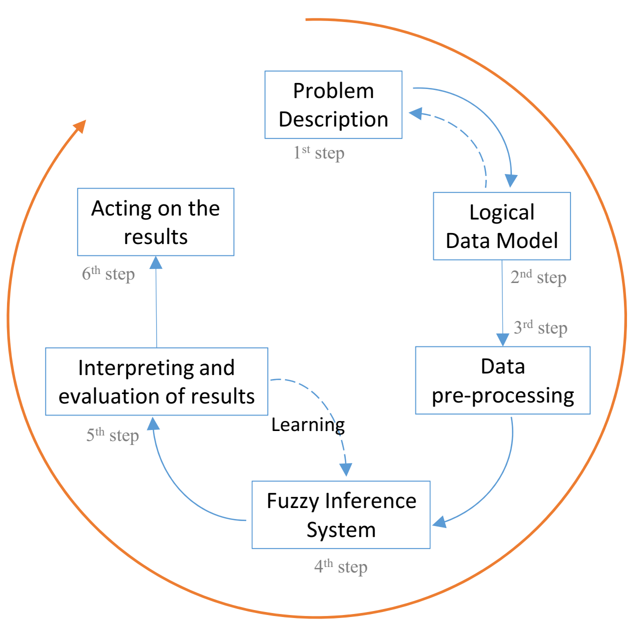


Fig. 1 The process of BI application

- P–S strategy;
- strategic fit between the strategy and the environment;

b. deployment.

In this article the deployment phase is out of the scope. The underlying assumption is that an idea for the P–S already exists, but no strategy has been further developed. Furthermore, due to service operations management principles [83], P–S are customer and market driven offerings, meaning that managers must have a basic comprehension of the market before starting the P–S strategy definition. During the planning phase of a P–S, managers of manufacturing enterprises in a MSE have to take three complex decisions:

The performance questions that have to be answered are the following:

a. *What are the optimal combinations among the Service operations competitive priorities (cost leadership, service differentiation* etc.*) to be combined into a P–S strategy (e.g. after-sales provide, outsourcing partners)?*
   It is assumed that there exists a certain pre-existing knowledge about the market, thus a general decision towards which competitive priority to lean is made in this phase. Based on the planned or proposed combination of competitive priorities, a P–S strategy is then identified. Hence, if the combination does not fit optimally the P–S strategy, managers can optimize the combination of competitive priorities, creating an effective and internally aligned P–S strategy.
b. *Are the assets, intangible and tangible, that are needed to compose and provision the targeted P–S according to its chosen competitive priorities available within the MSE?*
   At this point it has to be checked within the MSE, if the assets, tangible and intangible, are available to support such strategy. Namely, for instance, if the strategy is to offer highly-standardized remote maintenance, with low customer contact, the MSE must possess intangible assets like technological competences to set up such a system. This question thus deals implicitly with the concept of internal organisational fit, as it is viewed as a relationship between strategy and organizational components (internal variables) [80]. Organizational variables like processes and standards are all intangible assets of a MSE. If the needed assets are not available, the assets have to be obtained outside the MSE. After a potential alignment procedures, managers must scrutinize the P–S strategy that fits the market characteristics (environment), otherwise a strategy can hardly be effective. Thus, the next question arises.

c. *Does the targeted P–S strategy fits the market (environment) requirements?*
The answer to this lays in the concept of the external fit, hence in the fit between the P–S strategy and its environment (customer preferences, their sensitivity to price and quality, needs etc.). According to Ensign [80] the concept of fit is a useful one, but too often forcing managers to use the "rule of thumb" methodology. This approach enables managers to take more precise decisions. If the P–S is intended for a non-existing market, then the P–S strategy must simply be aligned with the business objectives, as the market requirements are non-existent. However, if the P–S is entering an existing market, then it has to be assayed if the P–S strategy fits the requirements of the market. If it does not, the strategy has to be optimized and retested afterwards. Finally, when the P–S will be on the market, a continuous alignment between the environment (market) and the P–S strategy has to be undertaken.

Using traditional DSS based on crisp inputs would not give high quality results, because: (a) the input data are in strategy definition often fuzzy (e.g. a more differentiated service than the competitor's), (b) in making such decision there is often not only one possibility, for instance at a level of 3.4 a strategy is acceptable and at 3.5 it is not anymore; it is more a matter of the degree of confidence [48].

4.2 Logical data model for P–S strategy planning

According to Kuper and Yardi [84] the logical data model is a generalization of Hull and Yap's format model [85], which generalizes the relational and hierarchical models, where database schemes are viewed as trees, in which each leaf represents data and each internal node represents some connection among the data. The aim of the logical data model is to enrich and detail the understanding of the business issues, data involved and their interrelations. It also represents an abstract structure of a domain of information. Once agreed upon among the project decision makers, the next step can take place. Moreover, it provides all parties a common understanding of the subject and problems, as it also enables to pin-point the added value of the planned BI information system. At this point no rules (e.g. if–then) are integrated, otherwise when changes in rules would occur, deeper and more complex changes would have to be performed in the information system, making it consequently very rigid, which is not in line with the context presented in this article. Thus Fig. 2 depicts the conceptualization of the data needed to plan a P–S strategy, as well as their interrelations that are needed to be understood for a sound decision making of an optimal P–S strategy. The logical data model follows the logic of first choosing the competitive priorities arising from new services, secondly choosing the strategic position of the P–S and thirdly relate this to an adequate positioning in the market. Hence the logical data model (Fig. 2) has three main levels and is described from a bottom-up perspective:

a. The first decision is to choose the optimal combination of competitive priorities arising from service operations. Thus a detailed representation of each of the seven possible competitive priorities arising from Service operations (Fig. 2:"Service operations competitive priorities"), which constitute the existing alternatives a P–S provider can choose from. The competitive priorities are the following: cost leadership, service differentiation, product differentiation, after-sales services, process oriented services, operational services and research and development. Each of those competitive priorities is then described in more details; for such relationship with the main competitive priorities a relation type called Aggregation was used. Different combinations of those Service operations competitive priorities constitute different Service strategies. The must optimal combination, where the elements fit best together, for a manufacturing enterprise, represents its first fit upon which it has to be decided. Hence, as different competitive priorities compose a Service strategy the relation Composition is used. The exclamation point in a road sign reminds of the need for such a decision.
b. The second decision lays in identifying the needed tangible and intangible assets needed to carry out the service operation according to the previously set-up competitive priorities. The search is undertaken at the MSE level and not at the enterprise level. This step partially verifies the feasibility of the planned strategy.
c. The third decision to be made is to scrutinize if the chosen Service strategy fits the targeted market. If the targeted market is an existing one, then the enterprise has to align its Service strategy to the market needs, but if the market does not yet exist, it must check if the Service strategy is really in line with the desired business objective. Usually it is a new non-existing one that has yet to be created, which is usually related to creating new needs; e.g. introduction of oat cereals for breakfast meant a completely new market for oat manufacturer at the time [86].
d. In the fourth step, based on the collected set of information arising from multiple sources, the manufacturing enterprise can choose from four specific Service strategies, through which it can position its P–S. Those are: (a) after-sales service providers,

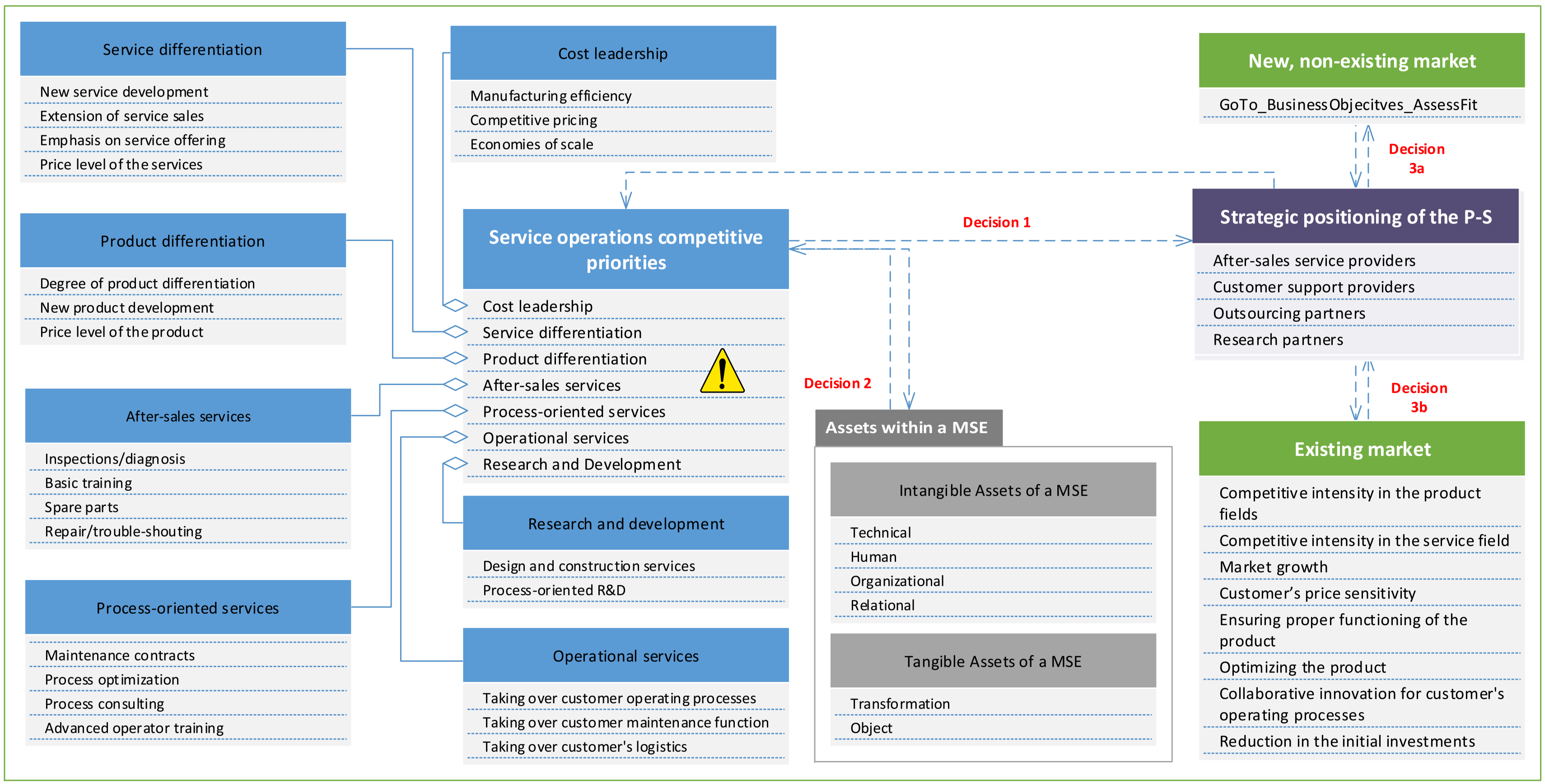


Fig. 2 Logical data model of the P–S strategy planning

(b) customer support providers, (c) outsourcing partners and (d) research partners.

We filled the database described in Fig. 2 with a random function based on a normal distribution, respecting constraints reported in the beginning of Sect. 5.

4.3 Data pre-processing

Most data pre-processing comes in the form of data cleaning, which involves dealing with missing information [11]. This step is relevant within a MSE.

4.4 A hybrid neuro fuzzy inference system for knowledge discovery

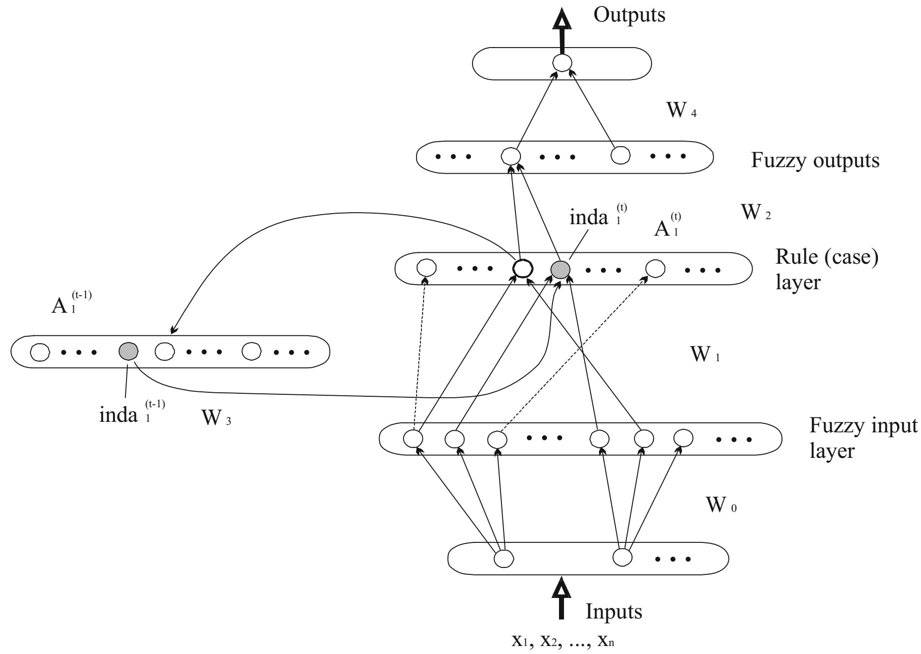
This section scrutinizes and develops the fuzzy based inferences system. First, the knowledge base is designed based on the Logical Data Model. It means to extract the linguistic variables and the linguistic terms. In the second step, the membership functions are constructed in order to map the non-fuzzy input values to fuzzy linguistic terms and conversely, as also to quantify the linguistic terms. Thirdly, the rules are designed, which represents the quintessence of the DSS, which are based on salient operations management principals and strategies arising from knowledge expert confirmed by empirical testing in the manufacturing sector. The robustness of the knowledge base makes the rules even more reliable as also the output. At this point software engineers in the MSE have all the knowledge and rules available to implement it in a DSS. Thus, in this section an inference for knowledge discovery is designed. In this paper we only propose a method based on a Neuro Fuzzy inference system (NFiS) and in particular an Evolving NFiS (ENFiS) called EFuNN [3] tailored for this problem described in chapter 4.2 using variables created above.

EFuNNs are learning models that can learn in an incrementally adaptive mode any dataset, regardless of the problem (function approximation, time-series prediction, classification, etc.) in a supervised, unsupervised, or hybrid learning mode, subject to appropriate parameter values selected and a certain minimum number of examples presented. Some well-established Neural Networks (NNs) and Artificial Intelligence (AI) techniques have difficulties when applied to incrementally adaptive, knowledge-based learning, for example catastrophic forgetting [87], local minima problem, difficulties to extract rules [3, 88, 89], are typical problems in multilayer perceptrons (MLP) and in backpropagation learning algorithm, not being able to adapt to new data without retraining on old ones, and too long training when applied to large datasets. The radial basis function RBF neural networks require clustering to be performed first and then the backpropagation algorithm applied. They are not efficient for incrementally adaptive learning unless they are significantly modified. Many neurofuzzy systems, such as ANFIS [90], FuNN [91], and neofuzzy neuron [92, 93] cannot update the learned rules through continuous training on additional data without suffering catastrophic forgetting. Several analysis and experiments [94, 95] shows that the EFuNN evolving procedure leads to a similar local incrementally adaptive error of other techniques e.g. Resource Allocation Network (RAN) and its modifications, but EFuNNs allow for rules to be extracted and inserted at any time of the operation of the system thus providing knowledge about the problem and reflecting changes in its dynamics. In this respect the EFuNN is a flexible, incrementally adaptive, knowledge engineering model. One of the advantages of EFuNN is that rule nodes in EFuNN represent dynamic fuzzy-2 clusters. Despite the advantages of EFuNN, there are some difficulties when using them, the major is that there are several parameters that need to be optimised in an incrementally adaptive way. Such parameters are: error threshold Err; number, shape, and type of the membership functions; type of learning; aggregation threshold and number of iterations before aggregation, etc. A possible way for solving this problem is a genetic algorithm (GA) use, better a cGA more faster [96, 97] used in this application. As part of future research an interesting issue could be a study about performance of optimization approach for solving this and other disadvantages. In the meantime results of the EFuNN application on the synthetic database built for testing our approach are presented in Sect. 5. In Fig. 3 [94] a classical EFuNN Architecture with on-line learning with a feedback connection is represented, we used this model in our experimentations.

While in the Fig. 4, a fuzzy inference system is depicted, where the underlined words signify the areas that the article covers.

Linguistic variables are the input or output variables of the system whose values are words or sentences from a natural language, instead of numerical values. Each member of this decomposition is called a linguistic term. Linguistic terms are almost invariably normalised (having a maximum membership value of 1), convex (having a single maximum or plateau maxima) and distinct (being restricted in their degree of overlap: often expressed as some variation on the concept that all membership values at any point in the universe of discourse sum to 1 across that universe) [98]. Linguistic variables [99, 100] are the building blocks of fuzzy logic [53]. The definition of the linguistic variables for the selected features can either be processed subjectively by questioning the experts, or determined empirically through statistical procedures [38]. In the case of this article, the linguistic variables arise from

Fig. 3 An EFuNN [94] with a feedback connection that works in an online learning mode



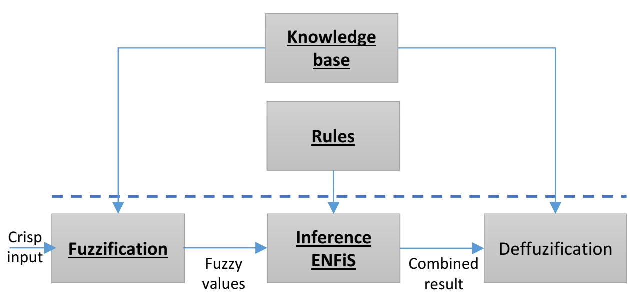


Fig. 4 Fuzzy inference system (partially based on Shapiro [53])

Gebauer's quantitative analysis, where all the variables have been statistically validated. Variables carry a range between 0 and 1 and are not necessarily constrained to such binary limits, where the value is subject to professional judgement. This subjectivity has profound implications for continuous system modelling, and is at the heart of the power and flexibility of fuzzy logic [101]. Table 1 depicts the linguistic variables involved within the decision making process of the P–S strategy definition.

To each linguistic variable, linguistic terms are assigned, being "Low", "Moderate" and "High". As for the input values for the competitive priorities, factor loadings from Gebauer's [4] clustering analysis creating the optimal clusters have been utilized. For instance, the linguistic variable *Cost leadership* in relation to different clusters of competitive priorities enjoys different factor loadings, as in the cluster emphasizing *Cost leadership and After-sales services*, it has a factor loading of 0.80, whilst in the cluster where *Service and Product differentiation and process-oriented services* are emphasized, and it has a very low factor loading of 0.25. Please let the reader note that all factor loadings can be found in Gebauer's article [4]. In the following Fig. 5 the relevant fuzzy set is depicted using trapezoidal membership functions [29, 48]. The aim of such graphs is to depict that one value of a variable that is comprised in multiple sets at the same time; for instance the variable *Cost leadership* can be at the same time *Moderate* and *High*. However, they differ in the degrees of membership, where the former enjoys a high degree of membership and the latter enjoys a lower one. Such exemplification is depicted in Fig. 5.

Afterwards, rules have to be defined. In the continuation, three sets of fuzzy rules are presented, whilst also one set of crisp IF–THEN rules related to the second decision that managers have to make, but it will be explained more in details next to the rules set. First the fuzzy rules set for the first decision is presented. The rules presented herewith will thus create what is referred to as the *knowledge base* [102]. The rules are expressed in the following form:

If (premise fulfilled), *Then* (conclusion valid).

The first decision that managers have to make is the following: "What combinations among the Service operations competitive priorities (cost leadership, service differentiation etc.) are optimal in order to fit a P–S strategy (e.g. after-sales provide, outsourcing partners)?"

As seen in the Fig. 2, there exist four main competitive priorities, which can be combined differently to position a P–S on the market. Each of this cluster has been obtained in Gebauer's [4] quantitative study. Only one rule per cluster is proposed, which is the optimal one. The business

Table 1 Linguistic variables involved in the decision making process

Decision	Linguistic variables	Abbreviation
1st	Service differentiation	SD
1st	Product differentiation	PD
1st	After-sales services	AS
1st	Process-oriented services	PS
1st	Cost leadership	CL
1st	Research and development	RD
1st	Operational services	OS
3rd	Competitive intensity in the product field	CI_PF
3rd	Competitive intensity in the service field	CI_SF
3rd	Market growth	MF
3rd	Customer's price sensitivity	CPS
3rd	Ensuring proper functioning of the product	PF
3rd	Optimizing the product in the customer process	OP_CP
3rd	Collaborative innovation for customer's operating processes	CINNO
3rd	Reduction in the initial investments	RII
1st and 3rd	After-sales service providers	ASP
1st and 3rd	Customer support providers	CSP
1st and 3rd	Outsourcing partners	OP
1st and 3rd	Research partners	RP

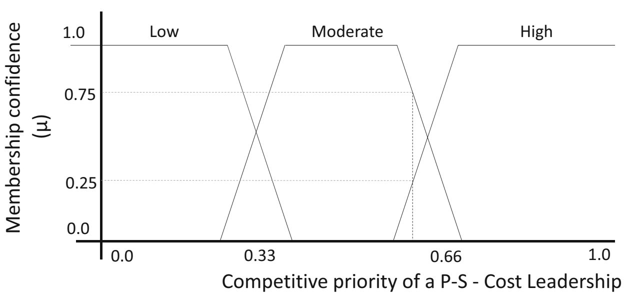


Fig. 5 Membership function for the variable *Cost leadership*

objective of a manager is to maximize its revenues and effectiveness, hence seeking to reach an optimal position. Those optimal positions, solely in terms of competitive priorities, are indicated by the rules presented hereunder. Furthermore, too many rules would have to be integrated into the information system.

At this point, if managers find out that their combination is not according to the identified clusters that are characteristics for manufacturing enterprises provisioning P–S, they have to restart and optimize the combination. The output of those rules serves as a natural input to the next rule-base. The next set of rules represents a crisp set of rules nested within the application of the Fuzzy inference system. Namely, after the application of the first set of rules in Table 2, managers must see if such assets, intangible and tangible, are available within the MSE to compose and provision the planned P–S. However, to obtain such answer, Boolean conditions value is satisfying, thus "true or false". Hence, the following table presents the main rules needed to perform the inquiry about the needed assets. Understandingly, it is presumed that a "bill of material" is pre-existing. The main question to answer is: "Are the intangible and tangible assets available to compose and provision a P–S according to its chosen competitive priorities?" The rules can be found in the next table.

If intangible and tangible assets were identified and that the manufacturing enterprises involved in the P–S planning within the MSE can compose and provision according to their targeted competitive priorities, then managers can

Table 2 Optimal combinations of competitive priorities

Rule #	Optimal combinations of competitive priorities	Competitive priorities						
		SD	PD	AS	PS	CL	RD	OS
1.	*Cluster 1_fit* Cost leadership and after-sales services	L	L	H	L	H	L	L
2.	*Cluster 2_fit* Service and product differentiation and process-oriented services	L	H	H	M	H	L	L
3.	*Cluster 3_fit* Cost leadership and Operational services	H	M	L	M	L	L	H
4.	*Cluster 4_fit* Service and product differentiation and R&D services	L	M	H	M	M	H	L

scrutinize their environment and choose a targeted market for their P–S. Hence, the next set of rules will help managers answer to the following questions: "Does the chosen P–S strategy fits with the market requirements?" Four clusters represent the identified types of markets with diverse combinations of eight characteristics constructs. Those combinations have been identified by Gebauer [4] through the already mentioned research. The results of the combination reflect the factor loadings; for instance *CI_PF* has a high fit with *Cluster 1,* where the factor loading with this characteristic was 0.92, which belongs to the range [0.67–1] and is considered as *high*. Such logic is applied to all the results of the rules listed in Table 4.

After identifying the market types, managers must benchmark the chosen competitive priorities for their P–S against the characteristics of the targeted environment (market) and scrutinize, if a fit exists or not. Based on the clusters forming different combinations of competitive priorities, Gebauer [4] could classify correctly 90.2 % of the enterprises from his sample. This result validates the combinations among the P–S strategy and environment (market) shown in Table 5. The results of those rules, depict four *high fit,* whilst to all others have been assigned *low fit*. This is because the most highly performing enterprises are encompassed, fit in those four combinations, while the others lower performing enterprises (eight out of 108) are scattered throughout the other clusters [4]. Consequently the results marked with *high fit*, should represent the objective of the managers, while all other combinations should be avoided, as those are linked with lower performance. Table 5 represents a fuzzy associative matrix [103], which is used to express rules in tabular forms. In this case, two dimensions are mapped, serving also as input for the rules.

To obtain results the process of inference is then performed. As for the step of interpreting the results, those will be done through the interpretation of the knowledge base, hence the P–S strategies. In such way the reader will be able to understand more clearly the value of those strategies and, as such, also of the rules that have been designed (for a detailed description of the strategies, please see Gebauer [4]). The first P–S strategy is After-sales Service Provider (ASP) and according to both inputs from the knowledge base, it puts extreme focus on cost leadership within a high competitive environment. This implies malfunctions. Therefore, such price sensitive customers expect standardized after-sales services, which are not included in the product price. The second strategy customer support providers (CSSP) is distinct by a low competitive environment, where customers expect that their machine breakdowns are prevented, thus predictive maintenance, which is in contrast with the previous strategy, where customers expect reactive maintenance. As for the third P–S strategy Outsourcing partners (OP), it is adequate for price sensitive customers that expect to reduce their initial product investment, but also have below average interest for proper functioning. The forth strategy Research partners (RP) is part of a low competitive environment with a strong focus on product and service differentiation and process oriented services (training etc.).

The following paragraph briefly exemplifies the potential usage of the set of rules designed. For instance a manufacturing enterprise of complex machine tools chooses to build on the competitive priorities of after sales services. This competitive priority can be found in combination of the cost leadership priority (see Table 2). The enterprise in question wants to build on those two competitive priorities by offering a predictive maintenance service for their machines, because machine downtime can be very costly for their customers. However, this new service must not increase the price of the product, as customers are not willing to pay a price premium. Hence, the manufacturing enterprise must see if the needed assets for offering such service are available within the MSE it is part of (see Table 3). Then if those assets are identified, it has to be reviewed, if the instances fit the needs at the required conditions, which in this case are availability and price. After this step, the machine tool manufacturer must check, if such P–S strategy fits the targeted market cluster (see Table 4). Namely, it has to be scrutinized if the new P–S strategy and its competitive priorities fit the characteristics of the targeted customers (see Table 5). In this case, the competitive priority of After-sales service providers, with an attention to costs, should target a highly competitive market where their customers are very price sensitive. Thus, it implies that the machine tool provider should pose special attention not to increase the price of the machine, while trying to reduce downtime. If the price

Table 3 Rules for identification of required intangible and tangible assets for a P–S

Rule #	IF	THEN
5.	I/TA for the planned P–S are available within the MSE	Analyse their instances
6.	The instances of the needed assets fit the needs	Go to next step in the decision making
7.	I/TA for the planned P–S are not available within the MSE	(Search for similar assets) AND (Search outside MSE)
8.	I/TA identified	Go to next step in decision making
9.	I/TA not identified	Go to previous step and modify P–S

Table 4 Rules to identify the environment of the planned P–S

Rule #	Identified combinations of environments (markets)	Market factors							
		CI_PF	CI_SF	MF	CPS	PF	OP_CP	CINNO	RII
10.	*Cluster 1*_fit highly competitive intensity and very price sensitive customers	H	H	L	H	H	L	L	L
11.	*Cluster 2*_fit low competitive intensity and concentrating on optimizing customer processes	L	L	L	L	M	H	L	L
12.	*Cluster 3*_fit highly competitive intensity and stung interest in reducing the initial investments	H	H	L	H	M	M	L	H
13.	*Cluster 4*_fit low competitive intensity and concentrating on collaborative innovations	L	L	M	M	M	M	H	L

Table 5 Aligned P–S strategies

Rule #	Identified combinations of environments (markets)	Optimal combinations of competitive priorities *(from Table 2)*			
		Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 4*
14.	*Cluster 1*	**H** (ASP)	L	L	L
15.	*Cluster 2*	L	**H** (CSSP)	L	L
16.	*Cluster 3*	L	L	**H** (OP)	L
17.	*Cluster 4*	L	L	L	**H** (DP)

of the machine would increase, some customers would possibly buy cheaper machines from competitors, as they could prefer some additional machine downtime, then a price increase. Hence, the machine tool manufacturer should review its P–S strategy in case a misalignment in the presented steps appears.

5 Experimental setup and results

In order to design an experimental setup, the limits of the model had to be previously defined. As it can be seen from the previous section, there are two main dimensions building the "optimal" clusters of a P–S strategy: (a) competitive priorities and (b) market factors. The intersections are represented in Table 5. The intersections between those dimensions represent optimal situations in regards to the business context; moreover there are four intersections that represent optimal situations (strategic fit) and are also forming a dataset that consists of 4 classes, and a compact input space, has been used, while the expression values of 400 cases (on records in the database) has been obtained as described in that section. The whole dataset has been divided into training and testing dataset for validation of a classifier system. These two sets came from different events potentially in different period. A suitable subset for strategic peculiarities has been chosen as training data set. The training data set had 200 cases samples. The test data set consisted of 200 samples. The test set shows a higher heterogeneity with regard to real problems presented in a business strategy scenario.

The task is: (1) to design a classifier based on these data selecting the right class; and (2) to find a rule profile for each classes. After having applied points 1 and 2 from the methodology above, different subset of input data have been selected. Several EFuNNs are evolved through the N-cross-validation technique (leave one-out method) on the data samples (EFuNN parameters as well are given in Table 6). In the case of data being made available continuously over time and fast adaptation on the new data needed to improve the model performance, this online modelling technique is particularly appropriate, so that new labelled data are added to the EFuNN and the EFuNN is used to predict the class of any new unlabelled data.

Different EFuNN were evolved with the use of different sets of input variables. The question of which is the optimum number of input for a particular task is a difficult one to answer and a wrapper method could be used, but it is not the aim of this manuscript. Table 6 shows an example of the extracted rules after all samples are learned by the EFuNN. The rules are 'local' and each of them has the meaning of the dominant rule in a particular subcluster of each class from the input space. Each rule covers a cluster of samples that belong to a certain class. These samples are similar to a degree that is defined as the radius of the receptive field of the rule node representing the cluster. For example, Rule 1 from Table 5 shows that 7 samples of class 1 have the objective of "Cost leadership" business strategy, while offering after-sales

Table 6 Results

Model	Errthr	Rmax	Rule nodes	Classification accuracy—training data	Classification accuracy—test data
EFuNN-1	0.9	0.4	6.3	87.4	80.0
EFuNN-2	0.9	0.5	4.0	95.0	92.2

services; of course, each of those 7 samples have diverse degree of fit. While for instance Rule 2 is based on offering such services that would differentiate the product.

One class may be represented by several rules, profiles, each of them covering a subgroup of similar samples. This can lead to a new investigation on why the subgroups are formed and why they have different profiles (rules), even being part of the same class (in this case for each of the four output cluster of our scenario). The extracted rules for each class comprise a profile of this class, our next issue will be visualize this pattern in a significant way. Seven samples of class 1 are similar in terms of having variables v1, v2 and v9 overexpressed, and at the same time genes v6 and v7 are underexpressed (Table 6)

Rule 1: if [v1] is (1 0.7) & [v2] is (1 0.85) & [v6] is (2 0.8) & [v7] is (2 0.87) & [v9] is (1 0.78) receptive field = 0.2 (radius of cluster), then class 1, accommodated training samples = 3/10
Rule 4: If [v3] is (2 0.68) & [v5] is (1 0.84) & [v6] is (2 0.95) & [v7] is (1 0.89) & [v9] is (1 0.88) & [v11] is (2 0.75) receptive field = 0.202 (radius of cluster), then class 2, accommodated training samples = 27/100

6 Discussion

IT capabilities contribute to a sustained competitive advantage by leveraging other organisational resources in such way that an enterprise is able to offer a product/service [104], whereas the analysis of data is essential in advanced value chain cooperation, by closing the information loop and providing a standardized data model [105, 106]. However, such systems still do not contribute directly to the process of planning the P–S strategy, which is extremely customized and intangible. Thus in this article a knowledge base, its dedicated fuzzy sets of rules were designed; those were then tested and applied by means of a technique based on an ENFIS method in order to build a DSS aiming at guiding managers in identifying essential information at the most relevant steps. Together, this enables them to optimize their P–S strategy and increasing its effectiveness and the performance of their enterprise.

The strength of the knowledge base is that it relies on established knowledge expert, that it was test and validated in this article. The BI rule set and its DSS based on the EFuNN/ENFiS method, enables to bring closer an immense knowledge set on P–S strategy and to operationalize it in a managerial decision process. Based on the synthetic data base that was built and tested using EFuNN/ENFiS method, it can be said that the results are valid. The focus of this article lays in the rules, knowledge base, inference system and learning capability depicted in Fig. 4, with underlined words that specify what was accomplished. It means that the defuzification has not been performed. Nonetheless, the presented sets of fuzzy based rules have the following limitations. As it can be noticed, only the optimal combinations are proposed, making all other alternatives inadequate. This means that a certain level of details has been lost. Nonetheless, the integration of such sets of rules would increase the complexity of the database essentially and would not bring the expected value. Namely, the value lies in the optimum positions, as manufacturing enterprises are seeking to maximize profit, thus seeking the optimum market position, which is represented by those rules (from a functional perspective). Another limitation is that the knowledge base relies on specific types of markets, thus potentially skewing the results of the usage within a DSS. While the main limitation is that the proposed set of fuzzy based rules have not been integrated into a DSS and applied onto the MSE level. This limitation can be seen as a path for further research. This would imply to identify the optimal inference system, for instance: Mamdani-type or Sugeno-type [107, 108]. The second research path would be to improve the decision support process in question, moreover related to the search of the assets within a MSE. Namely, the second performance question deals with the identification of the assets, intangible and tangible, within a MSE. Those assets are managed by means of MSE ontologies. However, it is not enough to only identify if an asset exists or not, but it has to be scrutinized, if it fits the requirements; for instance when querying for e.g. “with a highly experienced person in applying technical competency X”, the search result can be inefficient. Namely, when talking about intangible assets often natural languages are used to describe them, thus to improve the query in the MSE ontologies, the integration of a while fuzzy ontology reasoner would be adequate, although this research is still in its early stage [109]. Finally, the third research path would be, to see how such BI system could learn from the mistakes, how data could be easily inserted and/or updated by managers, who are not specialized in IT.

7 Conclusion

Information is being treated more and more as economic resources [110]. Also in the field of P–S it represents an additional layer of added value [111], thus all relevant information have to be identified and exploited accordingly by use of information system. Part of those represent BI applications, helping on one hand increasing the exploitation level of existing information, as also on the other hand to extract value from external data and thus reducing considerably the learning curve of managers. Based on a sample of European manufacturing enterprises [4], an expert knowledge base on P–S strategy planning was designed with its dedicated rules, and tested and validated by designing and testing a synthetic data basis using the method EFuNN/ENFiS, creating together a DSS for planning P–S strategy. Thus, developers of such DSS can identify the optimal solution for managers of manufacturing enterprises planning P–S within a MSE.

The fuzzy logic has been utilized in the rule set in order to increase the reliability of the results in strategic decisions making. Namely, one can imagine that inputs, for a strategic decision making, are hard to grasp and that a clear binary delineation, [0,1], does not depict the real world circumstances, strongly implying that such results would be of little value to managers. However by integrating fuzzy logic, this article has brought functional strategic decision making a step closer to human understanding and logic, thus increased considerably the reliability of the results and consequently their value. Furthermore, such DSS using this sets of rules can enable managers of manufacturing enterprises that have no experiences in service strategy to plan an effective P–S strategy in relation to their business environment. Even though that the field of P–S offer many opportunities for manufacturing enterprises to increase their long term competitiveness, it nonetheless offers also drawbacks and risks that have been identified by research as the "servitization gap". Consequently, such DSS enables to managers to reduce the risk of planning a poor strategy and thus considerably reducing their learning curve. Hence, the results of this article have contributed to partially automatize and standardize the complex decision making process of defining an optimal P–S strategy according to the business objectives. The next step would be to apply the DSS on multiple real industrial cases to further optimize the system.

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