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## Quantitative supply chain segmentation model for dynamic alignment

#### Rafael Alves Ferreira <sup>©a1\*</sup>, Lucas A. S. Santos<sup>a2</sup>, Kleber F. Espôsto<sup>a3</sup>

<sup>a</sup> Production Engineering Department, São Carlos School of Engineering, University of São Paulo, Brazil. <sup>a1\*</sup>rafael.alves.ferreira@alumni.usp.br; <sup>a2</sup>lucasalves02@gmail.com, <sup>a3</sup>kleberesposto@usp.br

#### Abstract:

Companies deal with different customer groups which makes it important to define the service level precisely and improve customer service through different supply chain strategies for each group. An alternative to deal with imprecision related to the segmentation processes suggested by either the Leagile or the Dynamic Alignment Schools is the application of fuzzy set theory. The objective of this work is to develop a quantitative model that uses the fuzzy set theory and, based on sales data, assesses the company's supply chain(s) to facilitate managers' decision-making processes to achieve dynamic alignment. It was possible to identify the supply chains that serve the client groups evaluated, providing answers faster than the analysis proposed by the models found in the literature. The application in two real situations validated the model. The results obtained were able to indicate managerial actions such as the establishment of clear processes for agile and campaign supply chains in one case or the improvement in the information sharing with a group of clients and thus moving from a fully flexible to the agile supply chain. To the best of our knowledge, this study is the first that aims to segment quantitatively supply chains in a company applying fuzzy set theory, providing a novel approach to align operations and supply chain strategy dynamically.

#### Key words:

Supply chain segmentation, supply chain management, fuzzy inference system.

### 1. Introduction

Supply chain management is a powerful approach to achieving competitive advantages and superior business performance in companies. The significance of supply chain management has increased due to the breaking of national and international borders, which grew the global movement of products and services (Routroy & Shankar, 2015). The set of relationships that typify the connections between organizations in a chain enables competitive advantages through cost reduction and market differentiation (Christopher & Towill, 2002).

It is vital to align the supply chain strategy with the countless demands of the markets. The "one size fits all" concept, that is, a unique strategy for the entire supply chain, does not apply to today's competitive environment (Gattorna, 2015; Godsell et al., 2011; Simchi-Levi et al., 2013). Yet, it is still possible to find examples of companies working in competitive and diversified markets that assume that the demands and purchasing behaviors are homogeneous (Hjort et al., 2016).

There are two schools for segmenting the supply chain (Godsell et al., 2011). The first school, called Lean-Agile, is based mainly on the characteristics of the products. At this school, Christopher and Towill (2000) introduce a supply chain segmentation model based on the combination of five market characteristics: duration of life cycle, the time window for delivery, volume, variety, and demand variability. Based on these characteristics, strategies

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for the supply chain are suggested. The authors advocate the existence of the three different types of chains: "lean", "agile", and the combination of these two, called "lean-agile".

For the authors of the first school, lean supply chains aim to serve the customer efficiently and at a low cost by removing all waste from the processes (Mason-Jones et al., 2000). Agile supply chains seek to integrate reconfigurable resources in an environment of intense exchange of information to meet customers' needs in uncertain markets (Yusuf et al., 2014). Lean-agile chains are the combination of the two previous options.

The second school, called dynamic alignment, aims to formalize the connection between marketing and supply chain strategy with a strategic approach. For this school, supply chain segmentation is the result of understanding the customer it serves. Consequently, the suggested segmentation method is based on customer behavior (Christopher & Gattorna, 2005; Gattorna, 2015; Gattorna & Walters, 1996). A member of this school, (Gattorna, 2015) proposed a model called Dynamic Alignment, which suggests five types of supply chains that work concurrently in companies, creating an environment of multiple supply chains.

Although the two schools of thought are consolidated in the scientific community and have a vast theoretical content, they still have a large gap concerning models that are not abstract and normative, with little empirical evidence (Godsell et al., 2011). The supply chain segmentation literature focuses on proposing segmentation criteria (e.g., volume, demand variability, variety). Thus, it lacks a robust solution for determining the segmentation parameters of these criteria (Fichtinger et al., 2019). An approach to cope with the vagueness of criteria proposed in the literature is the fuzzy set theory, proposed by (Zadeh, 1965). It has been applied in the decision-making process, as it can extract relevant results even based on uncertain or inaccurate input data (Banaeian et al., 2016; Fu et al., 2017; Lima Junior et al., 2014; Santos et al., 2017).

Supply chain performance management applies fuzzy logic inference rules to build models based on leading metrics and if-then scenarios (Ganga & Carpinetti, 2011). Analogously, supply chain segmentation is affected by uncertainty mainly due to the vagueness intrinsic to the evaluation of qualitative criteria and the imprecise weighing of different criteria by

different decision-makers. According to Renganath and Suresh (2017), decision-making techniques based on fuzzy logic are considered one of the best ways to work with imprecise or vague problems, in which the selection of alternatives is abstract.

The fuzzy set theory provides appropriate language wherein imprecise criteria can be handled, and it can integrate the qualitative and quantitative factors in the evaluation process (Lima Junior et al., 2013). Using fuzzy inference in decision-making has an advantage, the assumption of the approximate reasoning concept in the inference process that models human reasoning. Another advantage is capturing the experts' judgments in the knowledge base (Zimmermann, 1987).

Gattorna (2015) proposes a very detailed supply chain segmentation model based on customer buying behavior, supported by qualitative nature information, resulting in five possible supply chain types. On the other hand, Christopher and Towill (2000) suggest quantitative variables can be used as input to the segmentation process. This paper proposes a model that parametrizes a Mamdani fuzzy inference system (Mamdani & Assilian, 1975) to translate the input variables proposed by Christopher and Towill (2000) (time window for delivery, volume, and demand variability) into Gattorna's (2015) supply chain types: Collaborative Supply Chain, Lean Supply Chain, Agile Supply Chain, Campaign Supply Chain, and Fully Flexible Supply Chain.

In this context, this paper's main contribution is the development of a model that, combining the two supply chain segmentation schools, and supported by a fuzzy inference system, aims to reduce the abstraction and improve applicability. The present work uses sales data as input to assess and characterize the company's supply chains and, thus, facilitate the management decision-making processes towards the achievement of its supply chain's dynamic alignment.

Our research follows the empirical analytic modeling proposed by Bertrand and Fransoo (2002) ensuring a model that fits the observations and actions in the chosen environment. We use empirical data for the numerical analysis supplied by a multinational industrial machinery manufacturer and a Brazilian fertilizer mixing industry that serves two very distinct customer segments, thus, allowing the model assessment using real-world delivery lead-time, volume, and demand variability. This paper has been divided into six sections. In Sect. 2, we elaborate on the existing literature that addresses two schools of supply chain segmentation and the application of fuzzy set theory to it. Sect. 3 touches on the details of the methodology used, including the novel model proposal. The model application is explored in Sect. 4 and it is followed by the discussion in Sect 5. Finally Sect. 6 focuses on our conclusions and plans for future research.

### 2. Literature review

### 2.1. The DWV<sup>3</sup> Criteria

A significant contribution of the Lean-Agile School was the introduction of the DWV<sup>3</sup> market classification criteria by Christopher and Towill (2000) since the five criteria – duration of life cycle, time window for delivery, volume, variety, and variability – can be applied to target the supply chain strategy (Godsell et al., 2011).

Christopher et al. (2009) suggest the use of DWV<sup>3</sup> variables to classify products with similar characteristics. The principal output of this group is a clear definition of the requirements of each demand channel, together with the specific objectives to maximize competitiveness in each segment. Godsell et al. (2011) suggest a model that uses the variables volume and variability to define which supply chain strategy would be ideal for products, lean or agile. With these variables, together with the application of filters, the authors claim that it is possible to define the demand profile.

### 2.2. The dynamic alignment

Changing the focus from product to market, Gattorna (2015) suggests the concept of dynamic alignment, which is, that supply chains are constantly changing and require dynamism to remain aligned with the customers' needs. Christopher and Gattorna (2005) advocate the advantages of segmenting the supply chain along with buyer behavior, unfortunately, most organizations use internal parameters that provide little indication of how the customers want to buy products and services.

The key point for developing a supply chain that satisfactorily meets customers' needs is to understand the mix of the behavioral segments for a given market (Gattorna, 2015). This task, once performed, provides the possibility to segment customers so that

the appropriate value propositions are made to meet this scenario of multiple supply chains (Christopher & Gattorna, 2005). From these five purchasing behaviors, Gattorna (2015) proposed a model with five types of chain: Continuous Replenishment, Lean, Agile, Campaign, and Fully Flexible.

The model proposed by Gattorna (2015), despite being very normative, is inaccurate in the context of decision-making. The factors that are evaluated for choosing the best strategy for a given supply chain are based on opinions, therefore burdened with uncertainty and imprecision. The theory of fuzzy sets is an effective method for dealing with linguistic variables and decision-making in complex situations (Celik et al., 2015; Giri et al., 2022) and will be described in the next topic.

# **2.3.** Application of fuzzy set theory to the supply chain segmentation process

The bibliographic reference reveals that the task of segmenting the supply chain is not trivial. There are many normative models and few studies with applications in real environments (Godsell et al., 2011). The lean-agile school has three possibilities for configuring the supply chain, proposing variables related to products as a source of information for segmenting the supply chain. The school of dynamic alignment proposes a more robust supply chain segmentation model, nevertheless, the application of the model to the reality of companies is complex, mainly because it is based on questions that result in vague and inaccurate answers.

This work sought to combine the best characteristics of the two supply chain segmentation schools. A viable option was sought in the literature to deal with imprecision, applying the theory of fuzzy sets to the DWV<sup>3</sup> variables and taking advantage of the quality of the characterizations of the chains proposed by the dynamic alignment school.

### 2.3.1. Fuzzy theory

Conventional system analysis techniques are inherently inadequate for dealing with humanistic systems or any system in which complexity can be compared to a humanistic system (Zadeh, 1973). The fuzzy sets theory (Zadeh, 1965) has been used to model the decision-making process based on uncertain or inaccurate information, such as the judgments of managers or decision-makers (Lima Junior et al., 2014; Banaeian et al., 2016). Many applications of fuzzy sets theory can be found in the literature in the fields of Supply Chain Management, including production management, quality, and cost-benefit analysis, in which the unavailability of complete information, accurate references, and reliable data make them even more interesting (Kumar et al., 2013).

Rule-based models play a central role in fuzzy modeling while it captures relationships among fuzzy variables and provides a mechanism to link linguist descriptions of systems with their computational realizations (Pedrycz & Gomide, 2007), these are called the Fuzzy Inference Systems, discussed in the next topic.

#### 2.3.2. Fuzzy Inference System

The objective of a Fuzzy Inference System (FIS) is to control complex processes through human experience (Zimmermann, 2001). Complex systems involve various types of inaccuracies and represent a huge challenge for the development of models. This is especially true for the areas of business, finance, and management systems, which involve a large number of factors, some with socio-psychological nature (Bojadziev & Bojadziev, 2007).

The inference rules connect the input variables with the output variables and are based on the description of the terms of the fuzzy linguistic variable. The input variables represent the conditions and the output variables represent the consequences of the control rule (Zimmermann, 2001; Bojadziev & Bojadziev, 2007).

Mamdani and Assilian (1975) proposed a system capable of making Boolean logic more flexible when describing the states of processes through linguistic variables and using these variables as inputs to the inference rules. The Mamdani Fuzzy Logic Controller can be used as a decision support system (García et al., 2013) and has been used in a variety of problems such as life cycle analysis, supplier selection, and supplier performance evaluation (Lima Junior et al., 2013; Santos et al., 2017; Lima-Junior & Carpinetti, 2020).

The inference process begins with the assignment of terms for the input variables. In a system for evaluating customer satisfaction, for example, possible base variables are product delivery time, percentage of discount, and satisfaction. The "delivery time" variable could consist of the terms "low", "medium" and "high". The rules connect the input variables with the output variables and are based on the description of the state of the variable, obtained by defining the terms of the linguistic variables.

## 3. Methodology

In this work, we propose a quantitative model developed based on fuzzy logic to, based on selected input variables, enable the segmentation of the supply chain. Bertrand and Fransoo (2002) define that quantitative models are based on a set of variables that vary in a specific domain, whereas quantitative and causal relationships are defined between these variables. To the authors, the main concern of the researcher is to obtain solutions within a defined model and to make sure that these solutions can provide a greater understanding of the problem structure, as defined in the model.

For the development of the work, it was necessary to adapt the conceptual models DWV<sup>3</sup>, proposed by Christopher et al. (2009), and the dynamic alignment model, proposed by Gattorna (2015). The combination of these models served as a reference for modeling the rule base of the FIS.

The variables from the DWV<sup>3</sup> model were selected as the FIS input variables since they are numerical information highly available in most of the Enterprise Resource Planning Systems (ERP) available in the market. The criteria selected for the evaluation of the supply chain to be input variables were: the individual volume of each SKU sold to each customer, the variability of demand for each SKU per customer, and the average delivery time for the customer to be evaluated.

The other criteria, although they have an impact on the supply chain strategy, were not considered of primary importance. The stage of the life-cycle of a particular product does not directly influence demand planning, however, the volume and variability that the product presents at a given point in the life-cycle do influence (Godsell et al., 2011). For the model, the variety of items is also of secondary importance, since the inference system assesses the demand for each item individually. The identification of the variables can be seen in Table 1.

The inference system was developed to recognize the customer service patterns that have been being implemented. Therefore, the output variable of the selected fuzzy inference systems was the type of supply chain that is serving a specific customer or group of selected customers, based on the dynamic alignment model supply chain types, proposed by Gattorna (2015).

Five tables (Table 2 to Table 6) were proposed showing the characteristics' relationship of the time window for delivery, volume, and variability variables, based on the DWV<sup>3</sup>, applied to each of the five types of the supply chain of the dynamic alignment model. The linguistic variables selected to model the problem were "low", "medium" and "high".

#### 3.1. Fuzzy Inference System

The inference system adopted in the model is the Mamdani type since it is widely used and tested in the literature, according to Bojadziev and Bojadziev (2007) and Zimmermann (2001). The Mamdani Fuzzy Logic Controller was used because it is indicated for decision support systems (García et al.,

Table 1. Explanation of inclusion or exclusion of DWV<sup>3</sup> variables (Source: Adapted from Godsell et al. (2011)).

Variable	Explanation	
Duration of Product Life Cycle (Not included)	For reasons of simplification of the model, the product life cycle has not been included.	
Time Window for Delivery (Included)	The delivery time of the product is relevant to the need to use resources to meet the established deadline.	
Volume (Included)	It has a direct impact on the supply chain strategy.	
Variety (Not included)	The proposed model measures at the SKU level, so it is not relevant.	
Variability (Included)	It has a direct impact on the supply chain strategy.	

Table 2. Collaborative Supply Chain Characteristics (Source: Proposed by the authors).

Strategic Dimension	Characteristics	Source
Time Window for	Medium to high, the main value of the customer is	Gattorna (2015, p. 204)
Delivery	delivery on the agreed date and not specifically the length	Christopher and Towill (2000, p. 116)
	of delivery time	
Volume	Medium to low, since mature products tend to drop	Gattorna (2015, p. 203)
	consumption	Christopher and Towill (2000, p. 117)
Variability	Low, highly predictable through the communication	Gattorna (2015, p. 203)
	channel between supplier and customer. The product mix	Christopher and Towill (2000, p. 117)
	tends to be composed of mature products	

Table 3. Lean Supply Chain Characteristics (Source: Proposed by the authors).

Strategic Dimension	Characteristics	Source
Time Window for	Medium to high, the customer seeks a pre-established	Gattorna (2015, p. 243)
Delivery	delivery time, despite not sharing information on demand	Christopher and Towill (2000, p. 116)
Volume	Medium to high, since customers looking for the lowest cost tend to seek gains of scale	Gattorna (2015, p. 243) Christopher and Towill (2000, p. 117)
Variability	<u>Low</u> , transactional-minded customers tend to buy mature, established products	Gattorna (2015, p. 241) Christopher and Towill (2000, p. 117)

**Table 4.** Agile Supply Chain Characteristics (Source: Proposed by the authors).

Strategic Dimension	Characteristics	Source
Time Window for	Low, the demand nature requires a quick response	Gattorna (2015, p. 281)
Delivery		Christopher and Towill (2000, p. 116)
Volume	Low, lack of planning shrinks delivery times required to	Gattorna (2015, p. 283)
	meet demand and shrinks lot sizes	Christopher and Towill (2000, p. 117)
Variability	High, dynamic minded customers tend to increase the	Gattorna (2015, p. 283)
	range of choice. This large range generates high variability	Christopher and Towill (2000, p. 117)

Strategic Dimension	Characteristics	Source
Time Window for	High, since there is the entire product design, purchasing,	Gattorna (2015, p. 324)
Delivery	and manufacturing process, making it impossible to anticipate activities	Christopher and Towill (2000, p. 116)
Volume	Low, since the project's sale, in general, occupies a	Gattorna (2015, p. 322)
	large part of the manufacturing capacity for every single project.	Christopher and Towill (2000, p. 117)
Variability	High, each project has a specific customer and a different	Gattorna (2015, p. 322)
	product design.	Christopher and Towill (2000, p. 117)
Table 6. Fully Flexible	Chain Characteristics (Source: Proposed by the authors).	
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Table 5. Campaign Supply Chain Characteristics (Source: Proposed by the authors).

Table 6. Fully Flexible	Chain Characteristics (Source: Proposed by the authors).	
Strategic Dimension	Characteristics	Source
Time Window for	Low, for crisis solution the sooner the demand is met,	Gattorna (2015, p. 355)
Delivery	the better	Christopher and Towill (2000, p. 116)
Volume	Low, since demand will be met only once. In some cases,	Gattorna (2015, p. 354)
	the prototype is the expected delivery	Christopher and Towill (2000, p. 117)
Variability	High, it is impossible to predict what will be needed to	Gattorna (2015, p. 355)
	resolve a possible crisis.	Christopher and Towill (2000, p. 117)

## 2013) and has been applied in an endless number of cases in companies (Lima Junior et al., 2013).

The operator Gamma was chosen in the implication relation because it allows a compensatory effect in the implication, getting closer to the result found by the human decision system. For aggregation, the Mamdani model uses the maximum operator in aggregation.

For the implementation of the model's inference system, the FuzzyTECH 8.30c software was used.

#### 3.2. Identification of input variables

The terms of the input fuzzy variables in the inference system were represented by triangular and trapezoidal membership functions since they are functions with great computational efficiency and are simpler to be parameterized (Zimmermann, 2001). The number of terms for each variable is three, following the suggestion of (Von Altrock, 1997) who states that three terms are capable of simulating human thinking without generating the need for an excessive number of rules in the knowledge base of the inference system. The selected terms used were "Low", "Medium" and "High".

The parameterization of the inference system must be performed based on the analysis of the input data and the experience of selected specialists in the company. The variable Time Window for Delivery is represented by the average delivery time for a given item to the customer to be evaluated. The difference between the item's billing date and the date of receipt of the customer's order is used as the delivery time. The volume variable is represented by the total items purchased by the customer during the period to be evaluated. The variability was represented by the variation coefficient of each item purchased by the customer to be evaluated. The coefficient of variation is represented by the equation below, where  $\sigma$  represents the population standard deviation and  $\mu$  represents the mean.

$$CV = \sigma/\mu$$
 (1)

#### 3.3. Identification of output variable

The terms used as output variables were the names of the supply chains proposed by Gattorna (2015): Collaborative, Lean, Agile, Campaign, and Fully Flexible.

Considering the pattern recognition characteristic, it was decided not to defuzzify the results. As a result, the highest degree of membership found in the output vector was considered, defining the greatest similarity with a given type of chain (Von Altrock, 1997; Simões & Shaw, 2007).

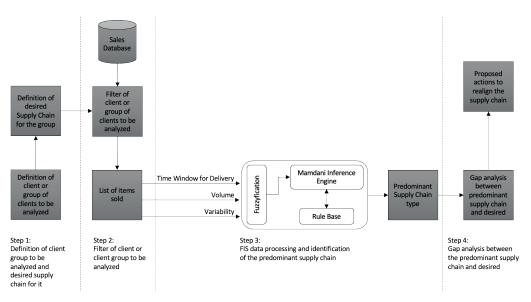


Figure 1. Supply Chain Alignment Assessment model (source: proposes by the authors).

#### 3.4. Definition of the inference rules base

The rule base of the inference system was based on the propositions of characteristics of volume, variability, and time window for delivery for each type of supply chain proposed by (Gattorna, 2015). Tables 2 to 6 were used to support the definition of the knowledge base. The full inference system rule block can be found in the appendix.

#### 3.5. The analytical model

The proposed model can be represented analytically in Figure 1. In the first step, the customer or group of customers to have its predominant supply chain type assessed is selected and it is defined which supply chain type has a better suit for them.

In the second step, the customer or group of customers who will be evaluated for which type of supply chain are currently submitted is filtered. It is necessary to obtain the sales information of all the items supplied in the evaluated period, generating a table with the items and their respective data of volume, variability, and average delivery time.

In the model's third step, the list is processed by the fuzzy inference system and outputs the predominant type of supply chain that currently serves the selected customer.

The fourth step of the proposed model is the analysis of the results obtained. At this point, decision-makers must identify the gap between the customer's current supply chain and the type of chain most aligned with the company's strategy. In this step, it is possible to recognize customers who are being over-served and customers who are not receiving the expected service. Input variables can be used as an indication of actions to be taken to realign customers with the service strategy.

### 4. Model application

To evaluate the proposed model, it was applied to two companies, from different fields. Empirical data for the numerical analysis and expert opinion was supplied by a multinational industrial machinery manufacturer, case 1, and a Brazilian fertilizer mixing industry, case 2.

#### 4.1. Case 1

The model was applied to a multinational company in the field of manufacturing machinery and industrial equipment. The company operates in several business models, one of which is the manufacture of equipment for sale, developing and adapting projects according to customers' needs, using the Engineering to Order (ETO) strategy. It also caters to equipment maintenance applications that are already running on the clients using the Make to Order (MTO) typology. The company attends sales orders for spare parts sold from stock using the Make to Stock (MTS) typology and has machine rental businesses, providing services in the Product-Service System (PSS) model.

#### 4.1.1. Model parametrization

To proceed with the input variables membership functions parameterization, specialists (see Table 7) were chosen. Those selected are experienced employees and have extensive knowledge of the company's processes and customers.

Initially, the supply chain alignment assessment model proposed in the work was presented to the experts. The concepts of fuzzy logic were also briefly presented to enable them to collaborate in the parameterization of the membership functions shown in Figures 2, Figure 3, and Figure 4.

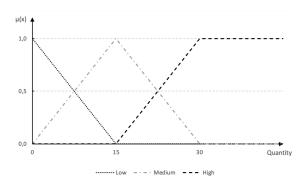
During this process, sales data for the past two years were consulted on the company's ERP system and tabulated on a spreadsheet. After analyzing the data collected in the system, a forum was opened for discussion and consensual definition of the parameters of the membership functions.

## 4.1.2. Data collection and assessment of supply chains

The group of experts suggested three groups of clients to be analyzed, considering data from the previous year. The first group of clients analyzed was the one that serves customers who bought machines in the previous year. The second is the group of clients

**Table 7.** Expert description (Source: Proposed by the authors).

Education	Experience	Role	Field
Bachelor	Over 10 years	Manager	Purchase
Bachelor	Over 10 years	Purchaser	Purchase
Bachelor	Over 10 years	Planner	Planning
Bachelor	5-10 years	Supervisor	Sales



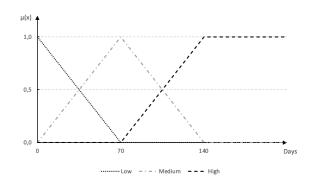
**Figure 2.** Volume membership function for Case 1 (source: proposed by the authors).

All data obtained were pre-validated by the company's experts. A search was made for possible incomplete fields or with a large discrepancy in results. Outliers have been removed to avoid distortion of the database.

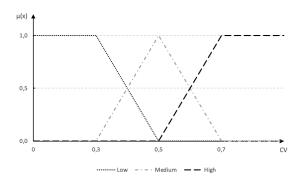
## 4.1.3. Evaluation of machinery manufacturing supply chain

The evaluation of the machinery manufacturing supply chain started with the application of filters in sales orders to locate all orders for machines billed in the previous year. A list was obtained with all the units sold, with varied construction complexities.

From the list of machines sold, the table was created with data on average delivery time, volume, and variability to serve as input data for the fuzzy



**Figure 3.** Time window for delivery membership function for Case 1 (source: proposed by the authors).



**Figure 4.** Variability membership function for Case 1 (source: proposed by the authors).

inference system. The result obtained by the system is shown in Table 8.

**Table 8.** Results from machines FIS (Source: Proposed by the authors).

Supply Chain Type	Quantity of Items
Agile	41 %
Campaign	50 %
Fully Flexible	9 %

To define the ideal strategy for the machinery manufacturing supply chain, experts concluded that a second segmentation should be carried out, between complex machines and simple machines. For the experts, equipment that requires many weeks of equipment design would have the ideal supply chain strategy as the campaign type, given that equipment design and manufacturing activities are concomitant for many weeks. The simpler equipment, on the other hand, has a short design time, so the agile supply chain would be the ideal strategy. In this case, by having a shorter design time, actions may be taken in a more organized way, since decisions regarding manufacturing processes are made based on a completed project.

## 4.1.4. Evaluation of supply chain for spare parts sales

In evaluating the supply chain for selling spare parts, the specialists selected a group with the five main customers of this supply chain. All orders for parts billed in the previous year were filtered, obtaining a list of 108 items sold. Sales data were then processed to obtain a table with the input variables proposed in the model. The results obtained when processing the data in the FIS are shown in Table 9.

**Table 9.** Results from spare parts FIS (Source: Proposed by the authors).

Supply Chain Type	Quantity of Items
Agile	81 %
Campaign	8 %
Fully Flexible	11 %

In the experts' assessment, the ideal supply chain strategy for this group of customers is the agile supply chain, since the variability of ordering items is high. According to them, customer demand for specific replacement parts is intermittent, making it impossible to maintain large safety stocks, both because of the high cost and the risk of obsolescence.

## 4.1.5. Evaluation of rental business supply chain

In the evaluation of the supply chain for the rental business, all orders for parts billed as maintenance items from the previous year were filtered, obtaining a list with 1122 different items sent to the field. Sales data were then processed to obtain a table with the input variables proposed in the model. The results obtained when processing the data in the FIS are shown in Table 10.

The supply chain that serves the spare parts of the leased machines showed a predominantly agile service profile. This result is consistent, given that there is a large installed base of machines for customers with many variations of equipment models, consequently different spare parts. The company has as a competitive advantage a high Overall Equipment Effectiveness (OEE), thus there is an effort to quickly replace parts with customers.

**Table 10.** Results from rental business FIS (Source:Proposed by the authors).

Supply Chain Type	Quantity of Items
Lean	1 %
Agile	72 %
Campaign	12 %
Fully Flexible	15 %

#### 4.1.6. Case 1 discussion

According to the company's experts, the results obtained by the FIS proved to be consistent. In the supply chain of the machinery manufactured by the company, two predominant types of the supply chain were found: the agile supply chain and the campaign supply chain. The machines served by the campaign-type supply chain are machines with greater complexity and long delivery times. The machines served by the agile supply chain are less complex. The engineering processes to which they are submitted are minor adjustments to adapt them to the needs of the customers.

It was noticed that some replacement items were served by a supply chain of the fully flexible type due to a temporary movement in the type of supply chain. We also found some items that were served by a campaign-type supply chain that were items used in machinery refurbishing, to perform maintenance on key machine components. When analyzing the results of data processing by FIS, it was noticed that 8 items, approximately 1%, had lean supply chain characteristics. From an investigation of the nature of these items, it was realized that they are items of consumption of equipment, such as lubricating oil and springs that suffer wear and tear, which represent a considerable cost for the company.

#### 4.2. Case 2

The second application of the model was in a fertilizer mixing industry located in a Brazilian northeastern state. The fertilizer commercialized by the company is sold regionally and has as its main customers small and medium farmers, local resellers, and sugar cane processing companies. The company operates in two business models, one is fertilizer sales through agreements previously firmed and the other one is through direct sales to customers on a first-come-first-serve basis. Both production strategies are MTO.

The company ERP system was designed exclusively for the company by a local provider, and implemented eight years ago, with an extensive reliable database. This system controls all sales and buying orders, storing data on customers and suppliers, delivery time, and volume negotiated.

The sales process is divided between direct sales and supply contracts. After the closing of the sale or the agreement, the orders are directed to the planning department, which verifies if the company can meet all the requirements of the closed sale.

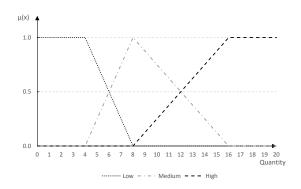
#### 4.2.1. Model parametrization

For the parametrization of the membership functions, the same process for parameters definition used in Case 1 was followed. The selected team for this assessment was composed of one sales representative, one commercial manager, and the industrial director (see Table 11). All selected employees were highly experienced with extensive knowledge of all the processes of the companies and their clients.

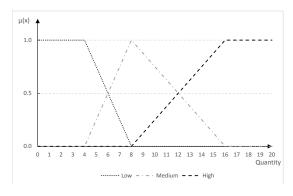
 Table 11. Expert description (Source: Proposed by the authors).

Education	Experience	Role	Field
Bachelor	5-10 years	Supervisor	Sales
Specialist	Over 10 years	Manager	Sales
Specialist	Over 10 years	Director	Production

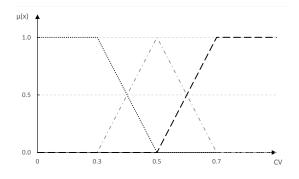
The membership functions are presented in Figure 5, Figure 6, and Figure 7.



**Figure 5.** Volume membership function for Case 2 (source: proposed by the authors).



**Figure 6.** Time window for delivery membership function for Case 2 (source: proposed by the authors).



**Figure 7.** Variability Membership Function for Case 2 (source: proposed by the authors).

## 4.2.2. Data collection and assessment of supply chains

The team decided that two groups of clients should be analyzed to evaluate the supply chains. The first group was composed of clients that firmed supply agreements in the previous year. The second is the group of clients who did not have firm supply agreements, composed of smaller clients with a buying behavior based on demand variation, most of them, local resellers.

All obtained data were validated by the company's experts before running the model.

#### 4.2.3. Evaluation of agreements' supply chain

The agreements' supply chain is composed of clients who need high levels of predictability in terms of supply and price. These agreements are usually made with clients who need a high supply volume and certainty that they will receive their product in the exact time needed. The product is delivered within an agreed lead-time between the order input and the product dispatch. For the analyzed year, supply agreements were 37% of the company's total demand.

The evaluation of the agreements supply chain started with the application of filters to locate all orders that were originated from supply agreements from the previous years. The obtained list had 42 different fertilizers formulas sold during the period. From this list, the table was created with the data with a lead time for each product, volume, and variability to serve as input data for the FIS. The result obtained is shown in Table 12.

Based on the results, the ideal strategy for the agreements supply chain only can be tailored after subsequent segmentation. As the experts' analysis, when supply agreements, which by its nature have higher volume, are agreed upon with few deliveries, campaign would be the ideal supply chain strategy type, given that the company must redirect its equipment almost exclusively to fulfill these orders, which are largely representative of the company's total demand. The other agreements, in which the deliveries are divided into smaller orders and consequently more deliveries, the supply chain

**Table 12.** Results from agreement FIS (Source: Proposedby the authors).

Supply Chain Type	Quantity of Items
Agile	36 %
Campaign	42 %
Fully Flexible	22 %

type based on the way that the demand was fulfilled would be the agile supply chain.

#### 4.2.4. Evaluation of resellers' supply chain

The resellers' supply chain is composed of smaller clients, mostly resellers and small farmers, and clients who did not want to firm the supply agreements. These clients have a buying behavior based mostly on the demand variation and need the product on a much lower scale than the clients of the agreements supply chain.

The evaluation of the resellers' supply chain started with the application of filters to identify the orders from resellers and small buyers from the previous years. All the clients that were not served by agreements were defined as part of this supply chain since their buying behavior is mostly the same. The obtained list had 100 different fertilizers formulas sold during the period. From this list, the table was created with the data with a lead time for each product, volume, and variability to serve as input data for the FIS. The result obtained is shown in Table 13.

**Table 13.** Results from resellers' FIS (Source: Proposedby the authors).

Supply Chain Type	Quantity of Items
Agile	52 %
Campaign	1 %
Fully Flexible	47 %

Based on the expert's assessment, the results were consistent but further segmentation is needed to understand the results for this supply chain, between common formulas and seasonal formulas. Common formulas are sold all over the year, with lower variability. Seasonal formulas are sold in highly specific time windows, which are linked to the rainfall regimen and the specific crop for that period.

#### 4.2.5. Case 2 discussion

The results provided by the FIS were consistent according to the company's experts. For the Agreements' Supply Chain, two predominant types of supply chain were found: the agile supply chain and the campaign supply chain. As the model proposes, the results of the supply chain are based on how the company attends the clients from different groups. For the company, the campaign supply chain is the right strategy for one part of the clients in the Agreements' Supply Chain, because of its characteristic small numbers of deliveries. However, the other part of the Agreements' Supply Chain is being served using the agile supply chain strategy although, according to the experts, using a collaborative supply chain strategy which would extend the delivery time to match the agreements.

For the Resellers' Supply Chain, two main strategies were identified: the agile supply chain and the fully flexible supply chain. According to the experts, both strategies are correct and further segmentation is needed to understand these results, into common formulas, with an agile supply chain strategy, and seasonal formulas, with a fully flexible supply chain strategy.

## 5. Discussion

In both cases, the experts agreed that the model was able to detect precisely and segment the multiple supply chains within the companies' systems according to their DWV<sup>3</sup> data.

In case 1, the company segmented its supply chain considering its business models and in a second step by client expenditure. They also have a list of key customers, defined by top management that has a preference in order fulfillment.

In the company, all processes share the same resources and, the model detected two main supply chain types: agile and campaign. One of the purposes of supply chain segmentation is operational efficiency (Wen et al., 2019) so the company could benefit from having a pattern to establish a clearer process for these two supply chain types. Another opportunity is on the lean supply chain detected. Although just a few SKUs, their value in the budget is high and they are products that don't suffer from obsolescence. An alternative for them is to improve information sharing in the chain and move from a lean supply chain to a collaborative one.

In case 2 the company segmented its supply chain based on the business models. The agreement supply chain has a big portion, 22%, of its orders classified on the fully flexible supply chains, the most expensive way of dealing with client orders. As the business model is based on formal agreements with clients the company has an opportunity to improve information sharing to increase demand predictability, making it possible to move to agile or campaign supply chains. Another opportunity is finding the customers that could have their variability reduced to move them to a collaborative supply chain.

On the Resellers' Supply Chain, due to the market conditions, the model pointed out that the segmentation in common or seasonal formulas is, at this moment, a good way to deal with orders.

## 6. Conclusion

The purpose of this work was to fill the gap regarding the complexity of applying supply chain segmentation models. The lean-agile school, despite suggesting practical ways of evaluating the supply chain for decision-making, only suggests three possibilities for the supply chain: lean; agile; or the leagile combination. This feature simplifies the view of the supply chain to the point of not segmenting it sufficiently, condensing types of chains with different characteristics within the same segment.

On the other hand, the supply chain segmentation proposal of the dynamic alignment school is more robust, with more segmentation possibilities. However, this school suffers from excessive regulation, in addition to the imprecision inherent in its evaluation process, which is primarily qualitative and difficult to apply. According to Godsell et al. (2011) the reasoning of the model in the two schools of thought on the supply chain design, lean and agile, and that of dynamic alignment, provides a holistic approach to the development of supply chain strategies.

The model proposed in this work aimed to group the strengths of the two supply chain segmentation schools and sought, as an alternative to cope with the imprecision related to the segmentation process, the application of the theory of fuzzy sets using fuzzy inference and the development of an expert system. The system uses the perception of experts to create a knowledge base that is used in the data processing.

The process of presenting the model to the companies' experts was an important factor in the parameterization of the fuzzy inference system. It was necessary to carry out training so that the results obtained in the parameterization were assertive. The disadvantage of this process is that the lack of expert training could compromise the results. The query of data in the ERP system, tabulation, and previous analysis favored the consensus on the parameterization of the FIS. Despite the apparent complexity of the fuzzy logic, the specialists felt comfortable with the definition of the parameters, using the steps proposed by Von Altrock (1997) to choose the values of the membership function. Future studies could investigate the inclusion of the Neurofuzzy technique to automate membership functions definition.

Contemplating the proposal of this study, the model was able to assess the current service standards of a selected group of customers, based on a set of quantitative data available in most ERP systems: the delivery time, volume, and variability. The quality and reliability of the ERP database proved to be an important factor in the consistency of the results obtained. The evaluation of a customer's current service level through a computational model collaborates with the seek for dynamic alignment. With the model, it was possible to identify the supply chains that serve the groups of clients evaluated, providing answers much faster than the analysis proposed by Gattorna (2015).

The model indicated managerial actions to realign the supply chain, for example, establishing a clearer process for agile and campaign supply chain, or fostering a collaborative supply chain in case 1. Another possible managerial action detected by the model was to improve information sharing with a specific client group could increase demand predictability and create a collaborative supply chain in case 2.

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Antecedents			Consequents	
Rule	Volume	Variability	Time Window for Delivery	Supply Chain Type
1	Low	Low	Low	Collaborative
2	Low	Low	Medium	Collaborative
3	Low	Low	High	Collaborative
4	Low	Medium	Low	Agile
5	Low	Medium	Medium	Agile
6	Low	Medium	High	Lean
7	Low	High	Low	Fully Flexible
8	Low	High	Medium	Agile
9	Low	High	High	Campaign
10	Medium	Low	Low	Lean
11	Medium	Low	Medium	Lean
12	Medium	Low	High	Lean
13	Medium	Medium	Low	Agile
14	Medium	Medium	Medium	Agile
15	Medium	Medium	High	Lean
16	Medium	High	Low	Agile
17	Medium	High	Medium	Agile
18	Medium	High	High	Campaign
19	High	Low	Low	Lean
20	High	Low	Medium	Lean
21	High	Low	High	Lean
22	High	Medium	Low	Agile
23	High	Medium	Medium	Lean
24	High	Medium	High	Lean
25	High	High	Low	Agile
26	High	High	Medium	Agile
27	High	High	High	Campaign

## Appendix I – Inference system rule block (Source: proposed by the authors)