Development of a Fuzzy Controlling Model to Measure the Leanness of Manufacturing Systems

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Abstract: Lean management has become an essential feature for the operation of industrial organizations. Measuring and analyzing lean manufacturing efficiency is a special and complex task. Management control systems should provide feedback on the degree of leanness for effective management and development. In our research we develop a lean manufacturing measurement model based on fuzzy logic, with a management control aspect. We build our model along lean KPIs and value streams. In our research, we highlight through a case study that a fuzzy controlling system can be an effective methodology for measuring leanness. Our results illustrate that the classification of different indicators, using different standardization norms, is not clear. During the analysis of the examined organization, the classification of several lean KPIs and value streams also changed, by changing the standardized norm. With this result, we point out that the definition of intervention points is not clear. The controlling aspect leanness index, developed in our research, allows us to express the expected performance of leanness goals as a function of organizational goals.

Keywords: modelling; controlling; leanness index; lean management; fuzzy logic

1 Introduction

The use of databases and data processing capabilities created by IT advances and innovation, especially Big Data and digitalization, are fundamentally changing control and management systems [1]. These innovative developments enable different reports to express the performance of an entire area or organizational unit in a single indicator. The creation of such aggregated indicators requires an appropriate and efficient infrastructure and the use of professional and mathematical methods [2]. Different evaluation algorithms and standardization norms are also required to interpret and make decisions based on the indicators [3].

One of the best researched of these aggregate management index is the leanness index. This is an aggregate indicator that can express the degree of leanness of the company under review [4]. Most studies agree and apply fuzzy logic to construct and evaluate the leanness index [5-7]. One of the bottleneck of modelling along this fuzzy logic is the selection of a standardized norm. Many studies choose the results of the best competitor in the industry to determine this norm [8-10]. However, a controlling system may not be able to apply this effectively and provide relevant information content to inform decision making.

Plan-fact analysis and dynamic feedback are essential elements of a modern control system [11]. Most lean fuzzy models are built along business aspects, using primarily validated financial data and do not include plan-fact analysis [4]. A lean fuzzy model with a controlling aspect should include corporate objectives and leanness results of lower levels (value streams). The model can be structured according to KPIs, measurement points and value streams. Under these conditions, the control system can gather information directly on the effectiveness of lean processes and identify intervention points to achieve the objectives. For a leanness index with a controlling aspect, there are several options available when choosing a standardized norm. Instead of the best of the industry competitor, it may be more relevant to choose the results of the direct competitor or the industry average. However, in business it is very difficult to obtain such sensitive data on competitor results. This in turn leads to the choice of a standardized norm based on internal information and structures. Such an internal norm could be the use of past period data, or plan data based on corporate objectives or strategy. On the basis of the plan data, it is possible to create a lean plan-fact ratio for each departments. Based on the result of the lean plan-fact ratio, it is possible to assess the leanness fact value in relation to the leanness plan value created as a function of the organizational strategy. The plan value cannot be considered as a crisp value, because its definition implies subjectivity and may therefore depend on several standardization norms. The values of this ratio are an excellent illustration of the development of the lean indicators and the aggregate lean index of the organizational departments in relation to the objectives. Taking into account the hierarchy of organizational structure, the plan-fact value of KPIs at a given level or the plan-fact analysis value of the whole organization can also be defined as a standardized norm. In our study, the values of the plan-fact analysis are included in the evaluation scale.

One of the bottlenecks in the controlling aspect model is the efficient definition of plan values. These values can be defined jointly, purposefully and with high subjectivity by strategic decision makers and operational managers with the support of the corporate governance system [12]. The other bottleneck is the algorithm that evaluates the deviations from the plan-fact analysis. This fuzzy algorithm must effectively evaluate both KPIs and different organizational units.

When examining the lean performance of different KPIs and organizational units, the controlling aspect model should predict the fact value in order to explore effective intervention points. The model must generate an extrapolated plan-fact ratio at all hierarchical levels. By interpreting this value, businesses may be able to intervene in areas that are expected to perform poorly relative to predefined goals.

In our study, we build a model for evaluating lean performance that is also suitable for achieving goals more effectively and for defining intervention points more precisely. The applied fuzzy logic creates an opportunity to deal with the subjectivity that results from the conceptual definition of lean and the subjectivity of the definition of lean goals. Fuzzy logic does not define exact values but blurs the values of indicators. This makes it possible to assess the subjectivity of inferential processes.

2 Literature Review

The lean approach can be used to determine what the value is. It is only the end customer who can decide what counts as value, and it is only possible to talk about value on the merits if a given product meets the needs of the customer at a given price and time [13]. And value is always created by the producer [14]. Lean manufacturing is not only a manufacturing system but also a manufacturing philosophy, paradigm and culture [15] that appears holistically among organizational functions and in this philosophy culture plays a more important role than the technical background.

With the application of the lean approach, the operations and processes that create value can be optimally sorted, and they can be performed more and more efficiently at the right time, in the right place, in the right quantity, without interruption [16]. This approach should not stop at the boundaries of a company, but should extend to the entire supply chain or the entire vertical of a given business line industry [13]. In addition to developing an economical system and production, lean management plays a very prominent role in shaping organizational culture and employee thinking by introducing an approach to continuous improvement [13] [17].

In the 21st Century, the application and implementation of lean management in the operation of management organizational processes is being used by many organizations and even appears to be a competitive criterion in many industries [18]. However, the effective implementation of lean management is not determined by the industry but by the nature of the processes [19]. Implementation can be successful in any industry, but tools need to be adjusted to the specifics of the sector and organization, and the philosophy needs to become part of the organizational culture. In order for lean transformations to be effective, it is necessary to incorporate the new approach into the already applied organizational culture [20].

2.1. Aggregation of Key Performance Indicator

The KPI (Key Performance Indicator) is a complex indicator that shows the effectiveness of various functional and strategic goals of a given organization [3]. There are KPIs defined at higher levels or formulated at higher levels. Aggregation of KPIs can be used to explore and evaluate the logical relationships between these hierarchical and vertical levels [3] [21].

KPI aggregation is a set of methodologies based on mathematical-statistical and logical correlations [22], applying which KPIs and indicators of different functional areas can be expressed in one indicator along a target value formulated at a given organizational level [23]. KPI aggregation can be a useful methodology in terms of the efficiency of processing indicators and statements with different functional and large data sets. [11].

The aggregation of KPIs related to lean management plays an important role. Appropriately defining KPIs is a kind of bottleneck, as lean operations and lean processes appear in isolation in the management processes of organizations [24]. Based on these, it is a challenge to measure the effectiveness of organizations lean management tools (kaizen, JIT, KANBAN, VSM, etc.) applying lean accounting methods. However, the appropriate defining of lean KPIs and the controlling models derived from them make it possible to determine the effectiveness of isolated lean processes and the leanness index [25]. This index can be created by applying fuzzy logic [8] and other methods of aggregation organized along logical correlations. It is a dynamic indicator that can be interpreted as an index suitable for characterizing organizational lean processes [22].

2.2 Leanness Index

The leanness index is a common method in the literature for measuring the lean performance of organizations. This leanness index is basically not a controlling method or a lean accounting method. In most cases, it covers the areas of corporate economics and supply chain management [25].

In most cases, the leanness index defines the lean extent of an organization in an indicator or as a fuzzy category [9]. Using a leanness index can not only express the lean performance of organizations. The lean performance of value streams, corporate functions, plant units, and supply chains can also be assessed with this leanness index. The two most commonly used calculation and evaluation systems are Dematel and fuzzy logic [9]. The lean fuzzy index is able to handle the subjectivity derived from the definition and evaluation of lean. However, controlling as an area is not able to effectively implement this method. The reason for this is that it does not necessarily correspond to the basic goals of controlling methods (goal orientation, bottleneck, future orientation, cost orientation, decision orientation) [12].

3 Methods and Resources

Through an extended case study [26] in our research, we develop a controlling aspect model measuring leanness effectiveness based on plan-fact analysis. The company in the case study is a factory unit of a multinational auto parts manufacturing organization. Data related to corporate processes is provided by the organization resource planning. We use this data in our model development.

To develop the model, it is necessary to determine the weight values of lean KPIs and the subjective values that correct for imprecise definition of plan values. The determination of the value that corrects the weight values and plan values is subjective, in our case determined by the opinion of lean managers and value stream managers. The values correcting the lean KPI weight values and plan values were measured by a questionnaire survey. The survey included 32 lean KPIs. The importance of these indicators and the accuracy of the pre-defined plan values were to be declared by the respondents. In our survey, we assume that both groups (lean managers and value stream managers) are equally likely to be able to judge and prioritize indicators and plans. The survey was conducted from 20.07.2020 to 03.08.2020. 24 people completed the questionnaire, 12 lean-logistics managers and 12 value stream managers.

In this paper we examine the superimposition and logical structure of different controlling methods and mathematical models in the lean controlling system of the examined industrial organization. Furthermore, we propose to build a model with a complex lean controlling aspect based on aggregated KPIs. Before applying the fuzzy-logic methodology for measuring leanness, we provide the following brief overview of fuzzy-set concepts.

3.1 Basic Concepts of Fuzzy Logic

Since the 1950s, the study of artificial intelligence has created various expert systems that draw inferences based on Boolean algebra based on a data and knowledge base [27]. Traditional binary logic is based on binary values: true-false. In the natural sciences and social sciences, however, in many cases there are phenomena that can be poorly or subjectively defined, it is not possible to model their operation with exact methods at all. In response to this problem, Zadeh developed the fuzzy logic method of the continuum with infinite set of values in 1965.

The meaning of fuzzy is vague, and as a result, classification into a given set in these systems is determined by membership functions. These functions illustrate the value of a particular linguistic terms [29], for example, the evaluation of a particular firm can be the values of a linguistic terms: poorly performing, moderately performing, very well performing. Thus, based on the former example, belonging to a given set can be determined using a function. This operation is called fuzzification [30]. The next step is to create a system of rules that performs actions and conclusions with the help of each linguistic terms. As a result of this process, an aggregate of member functions can be created, which is an essential element of de-fuzzification. During de-fuzzification, an actual value can be created and this can be considered the end result of the fuzzy analysis [28] [30].

The lean fuzzy methodology was first applied in 2008. The concept of lean fuzzy is based on the fact that the word lean as "leanness" is an adjective that has no crisp values that could be used as a general categorization. For example, "The lean level of organization B is better than the lean level of organization B" or "The lean level of organization C is excellent" and "This organization is lean acceptable" [8].

In this paper, we define the classification of a lean index as a fuzzy subset. To formulate a fuzzy-logical model, it is necessary to define the universe (U), the elements (xi) U, where U = {x1 + x2 + ... xn}, and the fuzzy subset A is included in U, where:

$$\mathrm{A} = \left\{\frac{x}{\mu_A(x)|x \in U}\right\}$$

The membership function of the fuzzy subset A is in most cases expressed as:

μ_A: U → [0,1], which assigns with each element of x ∈ U, the membership degree μx of x in

A: $\mu_A(x) = \mu x$

The most commonly used fuzzy-logic operations are intersection, union and complement:

- The intersection of two fuzzy subsets A and B: $\mu_A \cap \mu_B$ = minimum $\{\mu_A(x), \mu_B(x)\}$
- The union of two fuzzy subsets A and B: $\mu_A \cup \mu_B$ = maximum $\{\mu_A(x), \mu_B(x)\}$
- The complement of A: $\mu_A'(x) = 1 - \mu_A(x)$. [28]

3.2 Steps of Modelling

Step 1: From all the KPIs of the organizational controlling system, the KPIs influencing lean effectiveness and lean goals must be determined. These KPIs should be used for further analysis.

Step 2: Extrapolate the KPI fact values to the time point corresponding to the plan values

Step 3: Determining predictive ratios based on plan-fact analysis

Step 4: Evaluate the predictive ratios from the plan-fact analysis

Step 5: Evaluate the predictive ratio from the KPIs plan-fact analysis

1st test: Classification along predefined threshold values in an organizational control system (1. ST)

2nd test: Classification by deviation from the mean (2. ST)

Step 6: Evaluate the predictive ratio from the value streams plan-fact analysis

1st test: Classification along predefined threshold values in an organizational control system (1. ST)

2nd test: Classification by deviation from the mean (2. ST)

Step 7: Determination and evaluation of a leanness index based on predictive plan-fact analysis

1st test: Classification along predefined threshold values in an organizational control system (1. ST)

4 Results

The organization's control system consists of four hierarchical (Figure 1) levels. At the lowest level, there are measurement points from which the values of KPIs can be determined. Measurement points and KPIs are always linked to value streams. A value stream is any specific operation required to produce a particular product. In our research, we used the value streams defined by the examined company. These value streams operate as a separate organizational unit. The total value of KPIs represents the value of value streams. At the top level is an aggregate peak index, the lean index.

In our case study, we evaluate KPIs and value streams along two standardized norms (1. ST and 2. ST) based on plan-fact ratio ratios. Of these standardization norms, 1. ST = We perform the classification along subjective boundaries predefined by the organization for each KPI and value stream. 2. ST = We perform the classification based on the deviation from the weighted average of the value streams or related KPIs. In addition, a number of other standardized norms can be used for evaluation.

The values of KPIs, value streams, and leanness index are ratios derived from plan-fact analysis. The planned value of the indicators is pre-determined annual plan data during the strategic and operational planning of the company. We define fact value for a given period as extrapolated values. The data on the fuzzy rating scale will be percentages derived from the extrapolated plan-fact analysis.

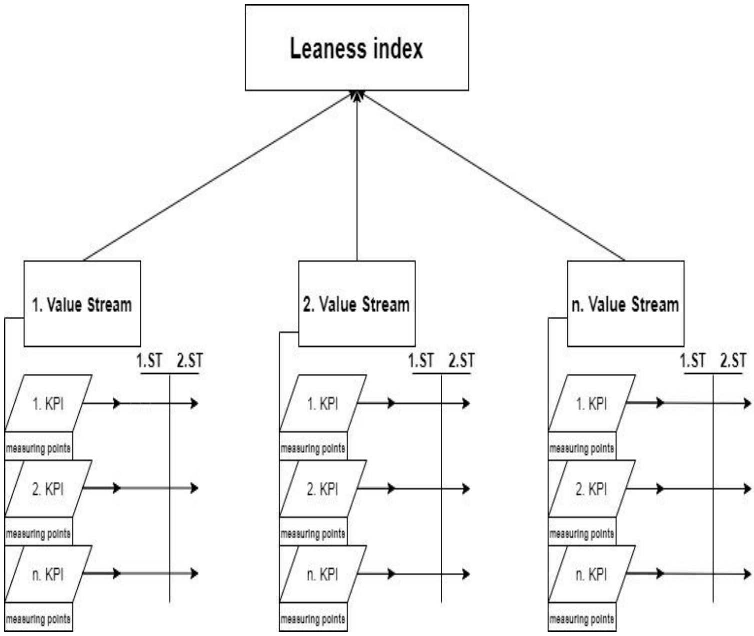

Figure 1
Controlling system (Source: Own Edition)

Step 1: Select KPIs that affect Lean performance

The organization uses a number of KPIs to measure performance. Of the KPIs used by the controlling system, we have identified 32 that influence lean performance. These KPIs can be calculated based on data from different measurement points. Table 1 shows the different lean KPIs that affect lean performance.

Step 2: Extrapolation of fact values

The fact value is the past period and current value of a KPI. In our analysis, we extrapolate the expected fact value at the end of month 12 based on the last 6 months of organizational lean KPIs. The fact values are defined as follows, taking into account the trend:

$$Z_{pred} = t - \lambda a$$

$$\lambda = \frac{\sum (a-\bar{a})(t-\bar{t})}{\sum (a-\bar{a})^2}$$

Table 1

Applied lean KPIs (Source: own editing based on the investigated company)

No.	KPI	Calculation mechanism
1.	**Purchasing efficiency**	$\frac{\text{Current purchase interval (pieces/minute)}}{\text{Average purchase time interval(minutes)}}$
2.	**Inventory speed**	$\frac{\text{Average stock (pieces)}}{\text{Production line operating hours(hours)}}$
3.	**Delivery on confirmed deadline**	$\frac{\text{Kanban orders completed on time}}{\sum\text{"Kanban order"}}$
4.	**Best quality suppliers rate**	$\frac{\text{Best quality suppliers (pieces)}}{\sum\text{Supplier (pieces)}}$
5.	**Transition time rate**	$\frac{\sum\text{Equipment changeover time}}{\sum\text{Shift normal hours}}$
6.	**In Process Kanban - IPK**	$\frac{\text{Average invetntory (pieces)}}{\text{Production line operating hours(hours)}}$
7.	**Relative time utilisation**	$\frac{\text{Current workforce(person)XTime spent creating value (minute)}}{\text{Current workforce(person)XAverage working hours (minute)}}\ \text{X } 100$
8.	**Production of the planned number of pieces**	$\frac{\text{Actual number of units produced (finished product)}}{\text{Bottleneck of the latest projected total number of pieces}}\ \text{X } 100$
9.	**Level of storage performance**	$\frac{\text{Completed orders x 100}}{\text{Orders received}}$
10.	**Relative production line utilization**	$\frac{\text{Number of pieces of undamaged product} * \text{product cycle time extension with changeover time}}{\text{Total time available for production}}\ \text{X } 100$
11.	**Average time spent in the storage process per part**	$\frac{\text{Time in storage in progress}}{\sum\text{part number}}$
12.	**Personnel costs per employee due to lack of availability of raw materials**	$\frac{\text{Value Stream Waiting Cost (Human and or Machine Cost)}}{\sum\text{Waiting time}}$
13.	**Average repair time**	$\frac{\sum\text{Time spent on repairs}}{\sum\text{Number of repairs}}$
14.	**Product lead time**	$\frac{\text{Fulfilling a specific order for a given product type}}{\text{Validated order date}}$
15.	**HPP (Hours per Product):**	$\frac{\text{Total working time (Human and or machine time)}}{\text{Number of product blocked}}$
16.	**P-Faktor (Performance Faktor)**	$\frac{\text{HPP X Number of products produced} - \text{machine time}}{\text{Constructive production time}}$
17.	**Outload**	$\frac{\text{Out load (\%)} = \sum\text{the lead time of a product}}{\text{Tacktime x 100}}$
18.	**Number of errors detected by workers**	$\frac{\text{Number of defective products detected by workers per value price}}{\text{Number of defective products per value price}}$
19.	**Number of requests for help and support for quality problems**	$\frac{\text{Requesting a quality manager}}{\text{Number of defective products per factory or per value price}}$
20.	**Number of errors detected by quality management**	$\frac{\text{Number of errors detected by quality management checks over a given period}}{\text{Total number of errors for a given period}}$
21.	**Internal error cost**	$\frac{\text{Cost of defective products}}{\text{Cost of all products manufactured}}\ \text{X } 100$
22.	**Percentage of products without defects on first production - FTT**	$\frac{\text{First production of flawless products(pieces)}}{\sum\text{Number of first productions (units)}}$
23.	**0 km error**	$\frac{\text{Returned parts}}{\text{All manufactured parts}}\ \text{X } 100.000$
24.	**Average time per person checked**	$\frac{\sum\text{Time spent checking, correcting errors (minutes) and/or cost (currency)}}{\sum\text{Number of staff (Person)}}$
25.	**Number of Q alarms per employee**	$\frac{\sum\text{Number of Q alarms}}{\sum\text{Number of staff (Person)}}$
26.	**Material yield variance**	$\frac{\text{Actual material use}}{\text{Expected material use}}$
27.	**Down time to operating time**	$\frac{\text{Down time}}{\text{Operating time}}$
28.	**Average profit per human resource**	$\frac{\sum\text{Profit}}{\sum\text{Number of employees}}$
29.	**Productivity rate**	$\frac{\text{Value added (based on number of units delivered)}}{\text{Staff capacity for cost centre}}$
30.	**Average overtime per human resource**	$\frac{\sum\text{Overtime}}{\sum\text{Number of employees}}$
31.	**Average unnecessary movement per human resource**	$\frac{\text{Leaving unnecessary workstations (pieces)}}{\text{Leaving a workstation (pieces)}}\ \text{X } 100$
32.	**Effectiveness of ideas implemented**	$\frac{\sum\text{results of phase projects completed in the period (number)}}{\sum\text{Expected results of ideas}}$

Step 3: Determining predictive ratios based on plan-fact analysis

Using plan-fact analysis, it is possible to standardize the various indicators in percentage form. The plan values are determined by the company's strategic decision-makers, lean- logistics managers, controllers and value stream managers. In most cases, these plan values are determined based on the company's past period, capacity, internal organizational data, and industry forecasts.

In our study, the fact value is an expected, extrapolated value at the same time as the plan date. The company subjectively evaluates the extent of the expected deviation from the plan value in order to process the information content and make effective decisions. This already assumes the operation of the fuzzy controlling system, although the ratio from the plan-fact analysis is crisp-like, as the plan value appears as a threshold. However, this crisp-like classification does not have enough information content to evaluate indicators and make effective decisions. Based on the value of the plan-fact ratio, the effectiveness of the KPI is only an indicator, it is ambiguous and there are no clear lines that can be interpreted as general classification. “Indicators A, B, and C are not expected to meet the plan value” and “The value of indicator A is critical” but “The value of indicator A is excellent compared to the value of indicator B”. This illustrates the fuzzy set theory developed by Zadeh in judging the expected performance of indicators. In our research, we illustrate the classification according to a standardized norm defined by the company and an additional possible standardized norm of our choice.

Step 4. Evaluation of predictive ratios derived from plan-fact analysis

The first standardized norm (1. ST) is based on a subjective assessment of the plan deviations defined by the organization. The ratios are classified into five classes according to the thresholds set by the organization. The classification of the limits is based on subjective choice and can therefore be interpreted as fuzzy logic.

Using the second standardized standard (1. ST), we point out that indicators classified according to 1. ST can be placed in another evaluation class with the same thresholds and ratios by changing the standardized norm. In this way it can be formulated that the assessment of the ratios is not clear.

As the 2. ST, we chose the deviation from the weighted average, which is the predictive fact value of the given value stream leanness. The weighting of the indicators expresses the contribution to the leanness value of the given value stream. In this way, the effectiveness of the indicator in relation to its own value stream can be evaluated. The weight values of lean KPIs were determined based on the subjective opinion of the organization's lean- logistics managers and the organization's value stream managers.

Assessing the opinions of these two groups is necessary because lean- logistics managers are able to determine the importance of a KPI at a general level, while value stream managers are able to determine the importance of a KPI at an operational level.

The two subjective opinions influence the weighting of the indicator to the same extent. The importance of a given indicator is assessed according to the given formula:

$$\xi_i = \frac{a_i + b_i}{2} \quad a, b \in [0,1]$$

where, a: value of importance according to the value stream manager, b: average importance according to lean- logistics managers, ξ: weight value obtained, i: serial number of the indicator.

The company has twelve value streams. For each value stream, an analysis of the values of the 32 lean KPI indicators is meaningful. The classification of lean KPIs along the different standardization norms is illustrated in Table 2. This table illustrates the results along the KPI data of the first value stream.

The function used for classification is structured as follows

$$\sigma_j = \frac{\sum \frac{A_{ji}}{N_j} \times \xi_i}{K}$$

where, a: predictive fact value, n: intended plan value, j_i: serial number of the examined element, K: KPI / Value stream examined element number, ξ_i: derived value of weight

The organization identifies the following five classes for evaluating the effectiveness of indicators.

$$T_j \begin{cases} \text{Critical} & \text{if } \sigma_j < -\alpha \\ \text{Not acceptable} & \text{if } \sigma_j \in [-\alpha; 1) \\ \text{Acceptable} & \text{if } \sigma_j \in (1; \alpha) \\ \text{Good} & \text{if } \sigma_j \in (\alpha; \beta] \\ \text{Excellent} & \text{if } \sigma_j > \beta \end{cases}$$

$$T_j \begin{cases} \text{Critical} & \text{if } \sigma_j < 0.95 \\ \text{Not acceptable} & \text{if } \sigma_j \in [0.95; 1.0) \\ \text{Acceptable} & \text{if } \sigma_j \in (1.0; 1.05) \\ \text{Good} & \text{if } \sigma_j \in (1.05; 1.1] \\ \text{Excellent} & \text{if } \sigma_j > 1.1 \end{cases}$$

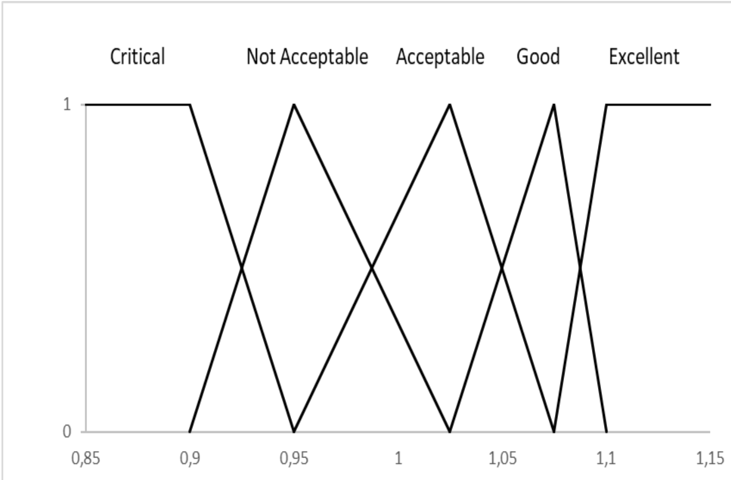

Figure 2
Fuzzy function (Source: Own edition)

Figure 2 illustrates the logical function represented by the predefined margin of error value and deviations of the organization. By applying the function, the company is able to evaluate its performance using different classification categories. The fuzzy function allows the control system to serve as an indexed feedback function for the company.

The function acts as a calculation methodology to evaluate and classify different KPIs, value streams and leanness index values. The classification is based on linguistic terms, which are defined by the company's controlling system and are used in this research. When applying linguistics terms to classes, it is not the value recorded on the scale but the thresholds and the standardized norms that are decisive.

Step 5: Evaluation of predictive ratios from the plan-fact analysis of KPIs

Our results show (Table 2) that by changing the standardized norm, KPIs can be assigned to another class with the same thresholds and ratios. In the first value stream, the KPI classifications of 7, 16, 19, 21, and 31 differ depending on the two standardized norms. The five indicators, which were given different ratings, changed from “Good” to “Acceptable”. This is an important feedback for the organization and for my value stream. After analyzing all twelve value streams, it is possible to identify the indicators that are classified as critical according to each standardized norm. Furthermore, the identification of the reasons for changes in the indicators that have changed class based on the results of the analysis can also provide relevant information. For both critical and reclassified indicators, monitoring of the processes measured by the KPI indicators is necessary. Analysis is an effective controlling method for achieving predefined objectives and plans.

Table 2
KPIs of 1. value streams leanness data table (Source: own edition based on the sales data of the investigated company)

Value Stream 1.					
KPI	**Plan-fact analysis deviation value (%) (1.ST)**	**Fuzzy category (1.ST)**	**Weight**	**Weighted deviation from the mean (%) (2.ST)**	**Fuzzy category (2.ST)**
1.	3.06	Acceptable	1.00	3.06	Acceptable
2.	2.04	Acceptable	0.75	1.53	Acceptable
3.	-3.12	Not acceptable	0.70	-2.18	Not acceptable
4.	-3.00	Not acceptable	0.60	-1.80	Not acceptable
5.	8.42	Good	0.60	5.05	Good
6.	-3.16	Not acceptable	0.70	-2.21	Not acceptable
7.	6.12	Good	0.65	3.98	Acceptable
8.	7.45	Good	0.70	5.22	Good
9.	2.04	Acceptable	0.75	1.53	Acceptable
10.	4.40	Acceptable	1.00	4.40	Acceptable
11.	8.70	Good	0.90	7.83	Good
12.	-4.17	Not acceptable	0.90	-3.75	Not acceptable
13.	-5.10	Critical	1.00	-5.10	Critical
14.	0.00	Acceptable	1.00	0.00	Acceptable
15.	-4.21	Not acceptable	0.60	-2.53	Not acceptable
16.	5.32	Good	0.60	3.19	Acceptable
17.	-3.23	Not acceptable	0.90	-2.91	Not acceptable
18.	-2.15	Not acceptable	1.00	-2.15	Not acceptable
19.	5.21	Good	0.60	3.13	Acceptable
20.	1.04	Acceptable	0.75	0.78	Acceptable
21.	6.12	Good	0.65	3.98	Acceptable
22.	-3.09	Not acceptable	0.80	-2.47	Not acceptable
23.	2.11	Acceptable	0.75	1.58	Acceptable
24.	-3.23	Not acceptable	0.75	-2.42	Not acceptable
25.	-10.00	Critical	0.65	-6.50	Critical
26.	-2.13	Not acceptable	0.65	-1.38	Not acceptable
27.	8.51	Good	0.60	5.11	Good
28.	1.04	Acceptable	0.60	0.62	Acceptable
29.	3.13	Acceptable	0.90	2.82	Acceptable
30.	6.12	Good	0.95	5.81	Good
31.	5.21	Good	0.70	3.65	Acceptable
32.	7.61	Good	0.90	6.85	Good

Step 6: Evaluate the predictive ratio from the value streams plan-fact analysis

The weighted average of the plan-fact ratios of the KPIs for a given value stream is the predictive fact value of the value stream. This value is compared to a plan value that is a correction plan value for the plan values of the KPIs. The corrected plan value was determined for each value stream based on the opinion of the company's lean logistics managers and value stream managers. Depending on the different standardized norms, indicators with outstanding values may have a “Critical” or “Excellent” classification. In this way, these outstanding values can be marked as intervention points. When monitoring the processes of the value stream, the plan value is reviewed, on the basis of which the predefined plan values of the KPIs can be corrected if necessary. In case the predictive fact value significantly exceeds the plan value, a positive correction or increase of the predefined plan value may be necessary. In case the predictive value is significantly below the plan value, a negative correction or reduction of the predefined plan value may be necessary. If there is no outstanding indicator in the prediction, depending on the standardized norm used, then a correction of the predefined plan values is not justified.

The value from the plan-fact analysis takes the position on the fuzzy rating scale. The value of the position on the scale is classified according to the already used fuzzy function and the two standardization norms (1.ST, 2ST,). In the analysis, the value streams are presented with the same weight value. The reason for this is that the organization does not differentiate between value streams, all value streams contribute to organizational performance to the same extent.

During the analysis of the organization's twelve value streams (Table 3), it can be stated that value streams 1, 3, 8, 9 and 10 were assigned to different classification classes with the same thresholds and ratios. From these results, it can be seen that the classification of the results is not clear. The definition of intervention points in the analysis of value streams is not clear either. In the case of the analysis of the value streams in Table 1, two value streams (3 and 8) were placed in the “Not acceptable” class, which raises the issue of more detailed monitoring of the processes. Value stream 1 was rated as "Excellent" in accordance with 1.ST. This can be assessed as an intervention point, as in this case the value stream may exceed the plan or corrected plan value.

However, in the assessment of 2. ST, value stream 1 is rated as "Good", which means that it performs only well compared to the average performance of the organization’s value streams. Comparing the two analyses, it can be concluded that the over performance is not that outstanding and therefore a revision of the plan values of the KPIs is not necessarily justified. Value streams 2, 5 and 11 are also classified as "Critical" according to 1. ST and 2. ST. This raises the possibility that the processes associated with the value streams and the plan values of the KPIs should be reviewed.

Table 3
Value stream leanness data table (Source: own edition based on the sales data of the investigated company)

12 Value Streams				
Number of V.S.	**Plan-fact analysis deviation value (%) (1.ST)**	**Fuzzy category (1.ST)**	**Weighted deviation from the mean (%) (2.ST)**	**Fuzzy category (2.ST)**
1.	10.32	Excellent	6.62	Good
2.	-8.17	Critical	-11.87	Critical
3.	2.13	Acceptable	-1.57	Not acceptable
4.	8.97	Good	5.27	Good
5.	-6.62	Critical	-10.32	Critical
6.	9.90	Good	6.20	Good
7.	9.63	Good	5.93	Good
8.	2.31	Acceptable	-1.39	Not acceptable
9.	6.40	Good	2.70	Acceptable
10.	6.83	Good	3.13	Acceptable
11.	-7.03	Critical	-10.73	Critical
12.	9.77	Good	6.07	Good

Step 7: Determination and evaluation of a leanness index based on predictive plan-fact analysis

The leanness index created expresses how the company is performing against its lean goals. The leanness index expresses the expected lean performance in an indicator. The predictive fact value of the leanness index is the average of the value streams. This predictive fact value is classified according to the fuzzy function already used and based on 1. ST. The classification based on 2. ST is beyond the scope of our research. Since in this case it would be necessary to determine the leanness index of all the company's units.

When ranked according to 1. ST, the corporate leanness index was classified as "Good" (Table 4). This means that the company is expected to perform well given the predefined lean objectives.

Table 4
Leanness index data table (Source: own edition based on the sales data of the investigated company)

Leanness index	
Plan-fact analysis deviation value (%) (1.ST)	**Fuzzy category (1.ST)**
6.18	Good

Conclusions

In our research, we have created a model of lean performance, with a controlling aspect, through a case study. We used fuzzy logic to measure manufacturing leanness. This method allows the use of linguistic terms. When using linguistic terms, it is not the value recorded on the scale, but the thresholds and standardized norms that are decisive. This allows the controlling model to more effectively identify outstanding values and judge them from different perspectives. We built our model along lean KPIs, which the examined company already used in its controlling system. In addition to these indicators, a number of additional lean KPIs could be used to build the model. KPIs were aggregated by value streams. The value streams have been developed by the company before, so they served as an appropriate level of aggregation in our model. Other units than value streams could also be suitable as aggregation levels. However, the use of value streams is advantageous because, in this case, lean KPIs can be structured more efficiently. The corporate leanness index is created by aggregating the values of value streams. Depending on the benchmark, the leanness index provides feedback on the leanness of the company.

Our model determines each indicator by plan-fact analysis. Fact value is the past and current value of a given KPI. In our research, we extrapolate the fact value of the plan date based on the past and current values of the indicators. A number of methods can be used for extrapolation to predict the fact value of an indicator. The plan value is a predetermined value for a future date. The planned value is a predetermined value, for a future date. For each KPI, the company under study formulates a planned value for the end of the financial year. The predictive fact value is compared with this plan value to produce the value of the plan-fact ratio.

In our analysis, we analyzed the data according to two standardized norms. The first standardized norm (1. ST) represents the thresholds from the plan-fact analysis defined by the company. The second standardized norm (2. ST) represents the deviation from the weighted average. By using 2. ST, we show that indicators classified according to 1. ST can be assigned to a different valuation class by changing the standardized norm, with the same thresholds and ratios. We illustrate with our results that by changing the standardization norm, the same KPIs and value streams are placed in a different classification category.

The model we developed can provide feedback on the effectiveness of the control system, value streams and lean KPIs, from a controlling perspective. The model can also be used to achieve lean objectives more effectively and to define intervention points more precisely. The disadvantage of the model is that extreme values significantly distort the accuracy of the analysis. Our fuzzy model does not formulate exact values, but gives fuzzy values and classes of indicators. These do not provide a sufficiently accurate answer in terms of formalizing inferential processes [27].

A possible further development of the model, is the extension of the lean KPIs included in the analysis, with lean performance indicators, related to other strategic and functional areas. It is recommended to extend the leanness index, with a management control aspect, for the whole supply chain. Another research opportunity is to implement the model we have developed, in other functional management areas. The future research may also include the use of the model for sustainability and financial markets analysis.

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