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Fuzzy set theory-based model for identifying the potential of improving process KPIs in production logistics area

Denisa Hrusecka [a]*, Department of Industrial Engineering and Information Systems, Faculty of Management and Economics, Tomas Bata Universtity in Zlin, Mostni 5139, Zlin 760 01, Czech Republic
Felicita Chromjakova [b], Department of Industrial Engineering and Information Systems, Faculty of Management and Economics, Tomas Bata Universtity in Zlin, Mostni 5139, Zlin 760 01, Czech Republic
Eva Jurickova [c], Department of Industrial Engineering and Information Systems, Faculty of Management and Economics, Tomas Bata Universtity in Zlin, Mostni 5139, Zlin 760 01, Czech Republic

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Abstract

The high complexity of today's manufacturing environment brings many problems with planning and managing, especially production, logistic and other key business processes. In many cases, it is quite complicating to identify the real causes of problems that enterprises face or to decide which one of them should be solved first. Especially, in the case of large enterprises, it is complicating to access expertise among all departments and employed professionals in order to solve the problems most efficiently. Our fuzzy model provides a simple tool for easy identification of the most significant problems of observed processes that cause their low performance according to the measured values of their key performance indicators. The model is based on data gained through interviews with production managers, industry experts and other professionals, and verified by real data from a model company. The results are presented in the form of case studies in this contribution.

Keywords: Production logistics, key performance indicators, KPI, productivity, problem identification, fuzzy set theory, process.

* ADDRESS FOR CORRESPONDENCE: **Denisa, Hrusecka,** Department of Industrial Engineering and Information Systems, Faculty of Management and Economics, Tomas Bata Universtity in Zlin, Mostni 5139, Zlin 760 01, Czech Republic
E-mail address: hrusecka@fame.utb.cz / Tel.: +420 736 120 790

1. Introduction

The production process is one of the most important key business processes of every manufacturing company. Its main goal is to create value that is required by its customers and eliminate non-value-added activities. In order to be able to improve processes continuously, it is necessary to monitor their performance through the set of measurable indicators. Wagner (2009) describes performance like the real subject's way of performing in comparison with the reference way of performing. This approach enables to measure also qualitative criteria through using some scaling methods. However, as Neely, Bourne and Mills (2002) confirm, many organisations still understand key performance indicators (further just KPI) merely like historical based financial indicators. They also highlight the necessity to consider the global company's strategy when defining KPIs. Setijono and Dahlgaard (2007) point out that the calculation of customer value may become a driving factor to continuous process improvement and it should be considered also when defining the process KPIs.

The problem of defining process KPIs is very complicated when some process objectives are contradictory (e.g., flexibility vs. efficiency). Therefore, while optimising processes, all potential changes must be guarded in order to avoid problems in other areas (Nyhuis & Wiendahl, 2009). Indicators that are used to assess, analyse and track manufacturing processes vary between different type of companies and industries. However, the majority of them are variants of the following common production KPIs: the number of products produced, scrap ratio, tact time, OEE – overall equipment effectiveness, productivity rate or machines downtime rate. Moreover, the production process performance is very strongly influenced also by logistics activities. Therefore, monitoring logistics performance is just as important as manufacturing or financial performance. Nevertheless, Toyli, Hakkinen, Ojala and Naula (2008) found that the overall level of logistics performance is at a very elementary level with almost no linkage to financial performance among more than 400 small- and medium-sized Finish companies analysed by his research team. Very similar results were gained also by Keebler and Plank (2009) among US firms, where the majority of respondents admitted that they do not comprehensively measure logistics performance despite the fact that it significantly influences their manufacturing performance or even their total financial performance. As we stated above and proved by many researchers, today's business environment is very complex and the performance of one observed process is influenced by the performance of many other internal or external processes. Green, Whitten and Inman (2008) pointed out the positive relationship between logistics performance and organisational performance within the manufacturing sector in their study and highlight the importance to measure also the performance at the supply chain level, since it influences the organisational performance quite seriously.

There are a lot of individual parameters that influence logistics or production process performance somewhat seriously. Very often just the most visible problems are solved, but the real causes for low performance remain hidden. Especially in today's very complex manufacturing environments, it is quite difficult and time-consuming to find the real cause of low values of performance indicators. The ability to solve production problems efficiently is very often undermined by special skills and the knowledge of individual specialists employed in the company, which should be accessible by all other employees with regard to continuous improvement. It is an ongoing challenge of many companies because the process of integrating varied perspectives of different experts and professionals is very complicated. Sometimes it is also employees' ignorance which negatively affects knowledge sharing and decision-making processes (Israilidis, Siachou, Cooke & Lock, 2015), especially longer tenured employees are very often negatively oriented towards donating their knowledge to colleagues (Cavaliere, Lombardi & Giustiniano, 2015). However, in most cases, it is just the lack of information, time and motivation itself.

An important aspect of production process improvement is also its sustainability. As Winroth, Almstrom and Andersson (2016) proved, the awareness and improvements of sustainability on shop floor level is influenced by the availability of a suitable set of indicators for its measuring. Therefore, they identified a list of performance indicators relevant for production managers divided into three basic dimensions: environmental, economic and social. The results of their study are very useful for our fuzzy-set based model extension and will be probably considered during the consequent research activities of the authors.

As stated before, sometimes it is complicated to identify the real causes of low values of performance indicators without deep analyses and accessing expertise among all departments. As Adamska and Minarova (2014) confirmed, the creation, development, use and evaluation knowledge is very important for each type of organisation, especially for its future development. The role of intellectual capital is increasing in the recent years and artificial intelligence methods and tools are more and more applicable also in the management and economics area. Salah and Moselhi (2015) used fuzzy set theory as an effective tool for contingency modelling in construction projects. They consider the fuzzy set theory model as an appropriate tool for providing experts with the flexibility of expressing their knowledge without the need to use historical data records. Therefore, fuzzy set theory is quite often used as a support tool for decision-making processes at all management levels. Despite the fact that it helps to interpret the experts' subjective judgments and transfer their knowledge, it also has its limitations, especially when the ambiguity of some information could involve certain level of hesitance (Pei, 2015).

The fuzzy set theory is very popular, especially in the healthcare area. Bayou, Reinstein, Du and Arya (2014) created a mathematical model for hospital cost allocation, which combines fuzzy set theory and the analytic hierarchy process, while Yuan and Herbert (2012) used fuzzy set theory for developing an application supporting remote patient monitoring and caregiver notification. In the healthcare area, fuzzy set theory is often used for designing medical diagnosis systems (Adlassning, 1986; Dagar, Jatain & Gaur, 2015; Hussain, 2010). This type of application can be easily transferable also to the process management area for identifying the main problems causing low values of performance indicators. Actual KPI values can be understood as symptoms of the low performance caused by several real causes – problems (diagnosis). The role of fuzzy set theory is to help managers make better decisions by providing them with expertise from all engaged departments.

The main goal of our contribution is to transfer experiences with fuzzy set theory-based algorithms from the healthcare area and other fields to production management and create a simple support tool for decision making.

2. Research objectives and methodology

The aim of this contribution is to demonstrate the possibilities of fuzzy set theory in the field of identifying major problems causing the low performance of selected production or logistics processes. Most of the problems in production or logistics involve an imprecise concept of what makes decision making very complicated. Even the right choice of major problems and constraints is often incredibly difficult. One of the simplest advanced tools that can help companies to handle this imprecise concept is fuzzy logic or fuzzy set theory. Since it is based on fuzzy relations, it allows users to describe the situation mathematically and clarify the relations between all critical elements of defined fuzzy sets. Our model is based on the max–min fuzzy composition (Zadeh, 1971), which provides a very simple but useful support tool for the decision-making process in this area.

In our problem, we have defined three sets:

- The set of analysed production or logistics processes $P = \{p_1, p_2, ..., p_m\}$
- The set of KPIs –$I = \{i_1, i_2, ..., i_n\}$
- The set of specific production problems, constraints, defects $D = \{d_1, d_2, ..., d_o\}$

There are some relations between all three types of our sets. The crisp relation between two sets is defined in fuzzy logic by its membership function noted as μR. Then, our three types of relations can be described as follows:

- Relation between the set of analysed production processes and their KPIs represent the relational concept 'very low value of KPI' and can be mathematically described as

$$R(P,I)=\begin{bmatrix} {}_R(p_1,i_1) \cdots {}_R(p_1,i_n) \\ \vdots \quad \ddots \quad \vdots \\ {}_R(p_m,i_1) \cdots {}_R(p_m,i_n) \end{bmatrix} \tag{1}$$

- Relation between the set of KPIs and the most probable production problems represent relational concept 'KPI is influenced by' and can be mathematically described as

$$R(D,I)=\begin{bmatrix} {}_R(d_1,i_1) \cdots {}_R(d_1,i_n) \\ \vdots \quad \ddots \quad \vdots \\ {}_R(d_o,i_1) \cdots {}_R(d_o,i_n) \end{bmatrix} \tag{2}$$

- Relation between the set of analysed production processes and the most probable production problems that have to be solved can be interpreted as a max-min composition of the previous two relations. It can be mathematically described as

$$R(P,D) \leftrightarrow \mu_R(p,d)=\max\left\{\min\left\{\mu_R(p,i),\mu_R(d,i)\right\}\right\} \tag{3}$$

First, the literature review and some structured interviews with production managers, industry experts and other researchers were conducted in order to achieve the main goal explained above. Together, 13 companies (Table 1 lists the profile of the participating organisations) provided us with very useful information that was used for designing simple fuzzy set theory-based model to identify the major problems causing low performance of analysed production or logistic processes.

Table 1. Profile of the participating organisations in qualitative reasearch

Company	The main line of business	No. of employees
A	Czech tyre manufacturer	over 500
B	Automotive producer of mechatronic door and seat systems	over 500
C	Producer of edible collagen casings	over 500
D	Producer of electronic HW and SW components	1 to 49
E	Producer of valves and fittings for potable water and sewage pipe systems	50 to 249
F	Producer of thermostats and other innovative regulators	over 500
G	Producer of corrugated board packaging	50 to 249
H	Producer of hospital beds	over 500
I	Semiconductor manufacturer	over 500
J	Engineering company	over 500
K	Producer of components for public transport vehicles	50 to 249
L	Tool manufacturer	50 to 249
M	Czech industry forging company	50 to 249

Our respondents were asked to state the basic KPIs that are used for monitoring the performance of their internal processes and all basic partial problem areas causing their negative values. The first step of analysis was conducted based on the Maxwell (1996) categorisation strategies. We established a list of categories of the most often repeated KPIs and observed problems influencing their final values. The results of the interviews were used for designing the above-mentioned fuzzy set theory-based model which was finally tested in one selected manufacturing company and is described below in the form of a case study.

Respondents were also asked to indicate the rate of influence of each observed problem to each KPI. Due to the fact that the opinions of professionals are very often subjective and they involve fuzziness, fuzzy set theory was considered as a suitable tool for identifying the main areas for improvement in the case of negative values of monitored KPIs. The main idea in this model is explained in the form of a case study below.

3. Results and discussion

Based on the literature review and results from conducted interviews with production managers, industry experts and other researchers, we set the following list of the most commonly used KPIs for assessing, analysing and monitoring manufacturing processes and internal logistics that are used in some form in all participating organisations:

- Number of products produced
- Error rate (in production area and internal logistics), in some companies defined as sigma value
- Total process lead time
- OEE
- Production process productivity
- Average production costs
- Average logistics costs
- Average inventory turnover
- Downtime rate

The above-mentioned list of KPIs is very general and obviously, some indicators are divided into several more specific ones which differ between companies. In the following case study, we focused only on internal logistics and therefore the used KPIs are more specific, but simplified for better interpretation of our proposed model.

3.1. Description of the case study and defined fuzzy sets

We used the form of case study for demonstrating our model with real numbers and explaining its main idea. In the future, this model will be extended to the form of standardised methodology applicable in all types of businesses for improving their processes. Our model company is a medium-sized enterprise producing car components with the main plant in the Czech Republic. In our example, we analysed selected internal logistic processes; more specifically, the processes of supplying selected production lines with purchased material. For simplification of our example, we did not consider material flows between individual workstations (however, in the final model, all the relevant internal processes are included of course). Therefore, the first set includes three members – the internal areas of our analysis:

- The process of supplying welding shop with purchased material (p1)
- The process of supplying pre-assembly lines with purchased material (p2)
- The process of supplying final assembly lines with purchased material (p3)

Each of the above-mentioned processes is continuously monitored through predefined KPIs in order to keep its required performance and efficiency. However, there are many factors that cause day-to-day problems and make achieving the required performance levels very difficult. The analysed company uses the following set of KPIs for monitoring the performance of selected processes:

- Average price (value) of inventory stored near the production line (i1)
- Productivity losses caused by unavailable material (i2)
- Average delivery time from placing an order to delivering items to the production line (i3)
- Error rate; for example: wrong type of material, quantity or others (i4)
- Number of individual deliveries/routes per shift (i5)

The value of the above-mentioned KPIs can be negatively influenced by many specific problems, critical points and process constraints, organisation or other defects, etc. The set of all potential problems will be called simply 'defects' in our study. We mention some of them that were observed during our investigation:

- Lack of communication between production workers and logistics workers (d1)
- Unavailability of handling equipment when needed (d2)
- Low level of respecting set rules and standards by employees (d3)
- Set rules or standards does not meet real conditions and requirements, not updated standards (d4)
- Lack of visualisation and 5S standards in warehouses (d5)
- Too much changes in production plans and schedules (d6)
- Lack of human resources – logistics workers do not have enough time to supply all workplaces on time (d7)
- Human mistakes while ordering material (d8)
- Human mistakes while preparing material for delivering to production lines (d9)
- Wrong or not updated information about finalised production and junks in enterprise information system (d10)

The impact of process defects to KPIs is represented by μR (d,i), and this is the point where specialist expertise is much necessary. On the basis of our previous research activities and the above-mentioned interviews with production managers and other professionals, we have divided this influence into several categories according to its rate. Each category was described verbally first and then replaced with the µ-value (Table 2) using the sigmoid method.

Table 2. The membership of fuzzy variables for all categories of the influence rate

The influence rate (fuzzy variables)	Membership μ_x
No influence	0.0474
Almost no influence	0.1192
Moderate influence	0.2689
Intermediate influence	0.5000
Rather strong influence	0.7311
Strong influence	0.8808
Very strong (definite) influence	0.9526

The membership of fuzzy variables in Table 2 was calculated according to the sigmoid membership function, which is represented by an 'S' shaped curve and is suitable for normally distributed data. It is defined by the following formula (Gorzalczany, 2002), where a = beginning of membership function and *c* = centre of membership function:

$$S(x;a,c) = \frac{1}{1+e^{-a(x-c)}} \tag{4}$$

Combining the membership values of the influence rate (Table 2) and the outputs of our qualitative study, we are able to describe the relation between the set of defined KPIs and the set of specific process defects (causes of negative values of KPIs) as follows:

$$R(D,I)=\begin{bmatrix} 0.8808 & 0.9526 & 0.7311 & 0.7311 & 0.8808 \\ 0.0474 & 0.7311 & 0.8808 & 0.0474 & 0.2689 \\ 0.7311 & 0.2689 & 0.2689 & 0.1192 & 0.5000 \\ 0.5000 & 0.5000 & 0.2689 & 0.2689 & 0.5000 \\ 0.1192 & 0.2689 & 0.2689 & 0.9526 & 0.1192 \\ 0.9526 & 0.7311 & 0.5000 & 0.7311 & 0.9526 \\ 0.2689 & 0.8808 & 0.7311 & 0.2689 & 0.2689 \\ 0.5000 & 0.1192 & 0.2689 & 0.5000 & 0.5000 \\ 0.2689 & 0.5000 & 0.0474 & 0.8808 & 0.5000 \\ 0.2689 & 0.5000 & 0.5000 & 0.2689 & 0.5000 \end{bmatrix} \quad (5)$$

For example, the first number (0.8808) means that there is a very strong influence between the lack of communication and the first KPI: average price (value) of inventory stored near the production line. Therefore, we can say that the lack of communication almost surely causes a high level of stored materials near the production line in the case of our model company. The influence rate can be different in different types of industries, but our long-term goal is to create some common methodology with standardised values for particular business types and industries in the future.

3.2. Problem solving using fuzzy set theory

In the next step, the relation between the set of analysed processes and their KPIs, identified in our model company, has to be described in the form of a fuzzy relation according to the observed situation. All the observed values of KPIs presented in Table 3 were first recalculated to the performance rate (*Px*) according to the preset target vales. For example, the value 0.80 in the first field means that the goal of welding shop is to keep inventory at the maximum total value of 2,000€ in the shop floor area. However, in the past decade, the average price of stored inventory was 2m500€. It means that the set goal was fulfilled from 80%. However, we need a negative interpretation of each KPI for our fuzzy model, where the highest value means a more serious problem – higher importance of this symptom and higher priority for future improvement. For this purpose, we used a simple reciprocal index where the new value is calculated as a 100% value to the desired value ratio. Based on the data gained from interviews, we set 100% membership of each KPIs at the performance value of 0.5, which means that the situation must be solved immediately. All other performance values were recalculated to their fuzzy set membership values (μx) in relevance to this basic one. For example, the performance value 0.8 represents a membership value of 0.625 (calculated as 0.5/0.8) in fuzzy set theory.

Table 3. Observed KPIs and their fuzzy set membership values

Index i_x	KPIs	Welding shop P_x	Welding shop μ_x	Pre-assembly P_x	Pre-assembly μ_x	Final assembly P_x	Final assembly μ_x
i_1	Average price (value) of inventory	0.80	0.6250	0.85	0.5882	0.70	0.7143
i_2	Productivity losses	0.50	1.0000	0.65	0.7692	0.70	0.7143
i_3	Average delivery time	0.75	0.6667	0.70	0.7143	0.80	0.6250
i_4	Error rate	0.95	0.5263	0.95	0.5263	0.80	0.6250
i_5	No. of individual deliveries/routes	0.70	0.7143	0.50	1.0000	0.65	0.7692

Then, the relation between the set of our three analysed processes (*P*) and their five KPIs (*I*) can be mathematically interpreted as follows:

$$R(P,I)=\begin{bmatrix} 0,6250 & 1,0000 & 0,6667 & 0,5263 & 0,7143 \\ 0,5882 & 0,7692 & 0,7143 & 0,5263 & 1,0000 \\ 0,7143 & 0,7143 & 0,6250 & 0,6250 & 0,7692 \end{bmatrix} \quad (6)$$

Finally, it necessary to identify the most probable production (or logistic) problems that cause the majority of low performance values and should be solved first. These problems were detected by using the following max-min fuzzy composition:

$$R(P,D) \leftrightarrow_R (p,d) = \max\{\min(0,6250;0,8808), \min(1,0000;0,9526), \ldots, \min(0,7143;0,8808)\} \quad (7)$$

$$= \max\{0,6250;0,9526;0,6667;0,5263;0,7143\} = 0,9526$$

After recalculating all the entries (all combinations of observed processes, indicators and defects) according to the above shown example for the process *p*1 and defect *d*1, we get the following relational matrix:

$$R(P,D)=\begin{bmatrix} 0,9526 & 0,7311 & 0,6250 & 0,5000 & 0,5263 & 0,7311 & 0,8808 & 0,5000 & 0,5263 & 0,5000 \\ 0,8808 & 0,7311 & 0,5882 & 0,5000 & 0,5263 & 0,9526 & 0,7692 & 0,5000 & 0,5263 & 0,5000 \\ 0,7692 & 0,7143 & 0,7143 & 0,5000 & 0,6250 & 0,7692 & 0,7143 & 0,5000 & 0,6250 & 0,5000 \end{bmatrix} \quad (8)$$

The PD relational matrix showed that the problem of the most serious production problems that causes low performance of all observed production and logistic process are:

- Lack of communication = highest value in the process of supplying welding shop and final assembly lines and the second highest value in the process of supplying pre-assembly lines
- Too much changes in production plans and schedules = highest value in the process of supplying pre-assembly lines and final assembly lines and the third highest value in the process of supplying welding shop
- Lack of human resources = the second highest value in the process of supplying welding shop and the third highest value in the processes of supplying pre-assembly and final assembly lines

Fuzzy set theory helped us to identify major problems, defects or areas for future improvement that should help co increase the performance of all observed processes in the company However, the whole model is dependent on the quality of input data. Fuzzy set theory is very helpful for solving complicated problems. Our problem was simplified for easier interpretation and description in our contribution. However, the whole model would have a much higher value for very complex manufacturing environments with a lot of potential threads negatively influencing the performance of their internal processes.

4. Conclusion

Our practical example interpreted via case study was quite simple and the problem would be easily solvable also without any sophisticated method. We used a limited number of KPIs and production defects in order to be able to interpret the main idea of our model. However, in real practice, the manufacturing environment is much more complex and the majority of production or logistics problems are caused by many different sub-problems which are sometimes detectable with significant difficulties. The process of solving these very complex problems is time-consuming and requires sharing expertise across the whole organisation. Our fuzzy set theory-based model should help to keep this expertise and provide the most probable reasons for detected inefficiencies in a very short time.

In the following phases of our research activities, the authors plan to create a complex fuzzy set theory model composed from two phases. The main idea of the first phase 'problem detection' was introduced in this contribution. In the second phase, the model should be able to propose suitable methods for solving detected problems based on lean specialist expertises.

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