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Fuzzy Signature Based Organization of Material Handling in Functional Production Systems

Abstract

The efficient management of material handling in a functional production system is just as complex as production scheduling. The costs of production losses are affected by the expertise and the decisions of the operative logistics personnel. Automation is one possible way of increasing the efficiency and decreasing the losses derived from poor human decisions. Although the total automation of material handling using robots and automated guided vehicles is technically possible, it is difficult to realize due to high standardization requirements. To improve efficiency, the replacement of human decisions with computer decisions is a feasible solution for existing companies, however, the exact mathematical modeling of such complex systems may be difficult since special knowledge and expertise is needed. The aim of the article is to present an easier computerized method by modeling human decisions of local experts using fuzzy logic. The fuzzy signature-based method is proposed, based on the operating practices of a real production plant. The experimental results compared with the mathematical optima given by linear programming are presented. The proposed optimization method is more simple than already existing ones, therefore it can be suitable for small and medium-sized companies.

Keywords: functional production system, job shop scheduling, material handling, automation, fuzzy signatures

INTRODUCTION

Functional production systems are widespread among small and medium-size companies due to their flexibility and relatively low investment cost. Compared to other production methods, it has lower efficiency and its scheduling is known to be NP hard. The situation is similar in the case of material handling. The efficiency of material handling strongly depends on the operators and forklift drivers. If the machines are idle the handling tasks are not performed in time, and this will adversely affect the production rate.

An integral, inseparable part of high value-added production systems is the movement of materials to and from productive equipment in the required time. With some production systems, e.g., in process production, material handling equipment is closely integrated. The conveyor belts are practically an inseparable part of the production equipment, like the storage places of the work-in-progress goods as well. This kind of production system is highly effective, but its production flexibility is moderate, so it is just suitable for mass-production with predictable demands.

Due to the high investment costs of process production systems, it is more flexible and the functional layout production system has a higher distribution among small and medium-sized companies. Here, the work item travels between the fixed shops. It requires a universal, independent, and flexible handling equipment, tailored to the characteristics of the goods to be produced by the plant. One of the duties of the material handling department in the operating system of the plant is to transport raw materials to the production equipment, half-finished items between each workplace, or finished goods to the warehouse within the required time frame. If the material handling tasks are not performed in time, production may be interrupted.

The automation of production machines is continuously improving, but traditional material handling (with verbal instructions and manually operated forklifts) is still the most common in functional production systems. One of the reasons may be that smart factory solutions with smart machines and smart forklifts are technically available on the market, although they require a very high level of standardization. This standardization has several requirements. One of them is to remove human decisions and replace them with a computerized decision-making system. Human decisions are very complex processes and they are influenced by numerous human factors. Some of these may depend on the personality or changes in the actual mood of the decision-maker. Naturally, they cannot be controlled or predicted. And, in most cases, the outcome is affected by local knowledge and experience. These may vary from worker to worker and they are time-consuming and costly to improve, especially when the turnover of employees is high. Furthermore, continuous decisions without clear rules will increase the stress of the workers. If the decisions are supported by a computer system, these problems can be reduced.

In this paper, we propose a novel approach to support the operative material handling decisions using fuzzy signatures. In the next section, we review the evolutionary levels of automation in material handling management then we provide theoretical background of computerized decision-making methods and fuzzy signatures in Sections 3 and 4, while the proposed fuzzy signature-based model is outlined in Section 5 and the experimental results are presented in Section 6.

1. AUTOMATION IN THE MATERIAL HANDLING OF FUNCTIONAL PRODUCTION SYSTEMS

The material handling methods used by different companies varies from country to country and place to place. These methods can be grouped in terms of various aspects. One of them is the level of automation. Owing to its importance, it is a widely researched topic that has produced several possible definitions and approaches (Frohm et al., 2008). According to these, the following evolutionary automation levels or groups of material handling can be defined.

- *Traditional management of material handling based on verbal information.* The operators of material handling equipment are responsible for material handling tasks of dedicated areas. In such systems the workload may not be evenly distributed between the different areas, and it requires local knowledge of the operators. Hence the rotation of employees between areas or the integration of the new employees into the system is time-consuming. Even so, because it does not require any directing system and a well-motivated employee with significant local knowledge can manage it quite successfully, it is a commonly used method. The disadvantages of this approach are the higher material handling resources and the critical effect of the subjective human decision that was already mentioned above. The stress level of employees - both forklift drivers and machine operators – may be affected by the poorly distributed workload.
- *Digitized tasks with manual decision.* This level requires the use of an electrical signaling system. The requests arrive at a central dispatcher who decides the proper order of the tasks for each piece of material handling equipment. If there is no central dispatcher, the tasks are visible for each operator and they have to decide the order of the tasks based on their experience. Balancing the workload subjectively might result in decreasing costs. A drawback is that it requires the standardization of information and defining all the processes, which is a significant challenge for several companies. However, this basic step is vital in order to evolve towards further levels.
- *Automated control of material handling* processes is possible if a digitized task handling system is available, and the given parameters of tasks are appropriate for computerized decision making. The decision making is very similar to the widely studied job-shop scheduling problem (e.g., linear programming [LP], priority dispatch rules, genetic algorithm). Here, we propose a novel approach based on the human method that was successful in the previous evolutionary levels, but it utilizes a less complex calculation model in the background than that for the existing operational research solutions. The realization of this level can lead to a significant improvement in efficiency.
- *Automated guided vehicles (AGV).* This high level of the automated logistics, where automatically guided material handling vehicles performing the tasks, is based on input data coming from the requester. The decision-making system may be the same as in the previous level but here there are no forklift drivers, only automated forklifts. This level has several requirements:
  - An available task management system.
  - Autonomous vehicles.
  - The environment of the plant must be able to support the AGVs (e.g., no floor defects).

- It has standardized carriers, packaging, pick-up and unloading areas.
- Last but not least, the working culture of the company should be amendable to change.

- *Automatized or smart factory.* The most advanced level is the totally automatized factory where production machines, robots and material handling machines work together without any human participation. It requires a very complex and integrated planning with clear goals. Due to the high standardization of the requirements, it is ideal when setting up new plants.

For existing companies, achieving of the second-highest level requires significant process reorganization and layout changes. The costs can almost be the same as the costs of setting up a brand new plant. Furthermore, this level of standardization could lead to a significant decrease in the flexibility of the plant. However, the second and third levels are attainable within a reasonable time and cost. Hence, it may be a good solution for small- and medium- sized companies if the wish to improve their processes and efficiency. In the following, we propose a fast and readily achievable solution for this.

A key point of our proposal is that instead of complex mathematical models and calculations, the computerized decision making process is based on expert knowledge and it can be maintained by the experts working in the company.

2. COMPUTERIZED DECISON MAKING METHODS

AGV-dispatching is an increasingly important area of advanced logistics (Rashadi et al., 2020). In contrast to human-driven vehicles, management of AGVs has to handle traffic of the vehicles systematically to prevent accidents, traffic jams, and deadlocks (Taghaboni–Tanchoco, 1995). Therefore, AGV dispatching has two main aspects. First, the scheduling of the tasks to achieve the goals of the system while minimizing the number of vehicles or maximizing utilization. Second, the routing of the AGVs to prevent collisions and deadlocks (Qui et al., 2002). These two aspects have a strong connection to each other, therefore none of them can be investigated separately. As a result, the methods used to dispatch AGVs are not suitable for the management of the material handling in the functional production system where human-driven forklifts are used.

Controlling material handling in functional production systems is quite similar to a job-shop scheduling problem, therefore its methods can be suitable for it also. The mission is to execute open tasks with clear deadlines and process times. Tasks have waiting costs that occur if the tasks are not performed before the deadline. Waiting costs increase linearly over time. Material handling equipment (for the sake of brevity, hereafter we use forklifts) can perform tasks according to their suitability and availability. Another parameter is the travelling time between the places of the tasks. The goal is to find the proper execution order and task distribution between the available forklifts in order to minimize the total waiting cost. In the literature, there are several methods available for this. Some relevant ones will be presented subsequently. These are priority rules, exact optimization methods, and approximate methods (Zhang et al., 2019; Chaudhry–Abid, 2016).

Priority rule-based methods are the simplest and the most commonly used and perform reasonably well in many instances (Sculli–Tsan, 1990), (Sels et al., 2011). In the case of such a complex problem as total weighted tardiness, they usually cannot provide adequate solution. However, Emmons (1969) proposed a lovely algorithm for minimizing job tardiness. His method is based on the relationship between the parameters of the jobs. The biggest drawback with his method is its excessive complexity. It requires too much sorting and logical steps to calculate the priorities between the jobs.

The exact methods, e.g., linear programming or bunch-and-bound methods provide a mathematical optimum (Razaq et al., 1990; Sen et al., 2003). Linear programming is one of the best known exact methods. It is widely used in problems where relationships between the objective function and the constraints are linear. However, it gives an exact solution, it needs special solver programs, and it requires special knowledge to configure and keep the models up-to-date. It also requires consistent data and an accurate formulation of the target function. If any of these change, it may require a complete redesign of the model.

Another group of methods is called the approximate methods. Although they do not provide optimal results, they give reasonable good solutions within limited time and use significantly fewer calculations. They act like the natural selection process to determine a proper combination and values of variables, providing continuously improving results. Their great advantage is that they are able to produce results within a reasonable period of time, even in the case of high complexity in the given problem (Pezzella et al., 2008; Gonçalves et al., 2005). Their disadvantages are that they require special, accurate modelling and precise input parameters for real-life situations.

Artificial intelligence solutions, based on machine learning can also handle large amounts of data relationships that are opaque to the human mind and predict events to a good approximation (Nemeth et al., 2016). However, due to the large amounts of the required teaching samples in problems like job-shop scheduling they are rather inappropriate.

The common problem of the exact and the approximate methods is that specialized knowledge is required to implement and manage them. The expert who is responsible for the system has to understand the production processes and has to be familiar with the logic of optimization methods. This knowledge is not common and may not be available for the small- and medium-sized companies. The less educated users also have to accept the results of computerized decisions. In the case of a sophisticated and hard to understand calculation, trust in the system may be questionable. Moreover, special software is required. In addition, an expert is needed, who can make the necessary modifications when it is required. Due to constant changes in the life of small- and medium-sized companies, this can result in the model having to be constantly readjusted. This will decrease the efficiency of the system and increase its operation costs. Therefore, in a real-life situation, a very flexible and simple calculation is required that can be adjusted locally and the users should understand its way of working or logic.

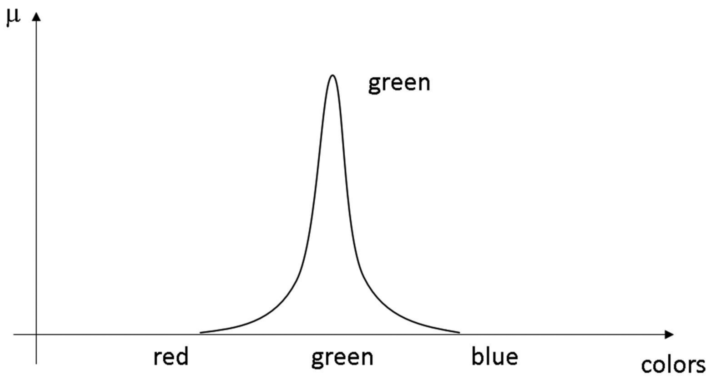
Fuzzy inference systems handle problems in a similar way to human thinking. Fuzzy logic is able to handle general logical connections, hence it provides a flexible solution for complex decision-making situations where numerous variables are related to one another using the logical terms AND and OR. Fuzzy logic is widely used in engineering and to support decision making in business (Carlsson et al., 2012). Linear programming using fuzzy numbers is one known solution (Rommelfanger, 1996; Fuller, 1998; Kumar et al., 2011) but the methods used for calculations can vary due to the “shape” of the fuzzy numbers. Therefore, using this method requires special knowledge and special software, so the problem is the same as in the case of LP with normal numbers.

A combination of fuzzy decisions and priority rules are used by Ahmed et al., in their 2016 study. Their method yields good results compared to traditional priority rules, but the large number of rules used can make real-life applications inflexible and difficult to adopt.

3. FUZZY LOGIC AND SIGNATURES

Fuzzy set theory was introduced by L. A. Zadeh in 1965. The basic idea is that the membership of a phenomenon in a fuzzy set cannot only be described by 0 and 1, but by any value between them. The membership value (m) tells us to what extent an element is a member of a fuzzy set, not whether it is a member at all. For example, according to this, all the colors are members of the green fuzzy set, but some are stronger and some are weaker. Figure 1 shows the membership function of a fuzzy set of green colors.

Figure 1 A possible fuzzy set of green colors



Source: Own compilation

However, quite good fuzzy inference methods exist for handling problems with complex logical relationships, like Mamdani–Assilian's (1975) or Sugeno's (1985) methods, especially in particular cases, where the aim is the fuzzy quantification of a phenomenon with well-known sub-properties. Fuzzy signatures are a generalization of vector valued fuzzy sets (vector-valued fuzzy sets), which are collections of fuzzy valued properties (Kóczy et al., 1999). Fuzzy signatures are such vectors, where the elements may or may not be fuzzy vectors themselves. In this way, quite complex dependency structures can be readily described and evaluated. Graphically, dependencies are depicted as tree structures, where the given phenomenon is the root and the nodes are devoted to its sub-properties. Of course, the structure contains mathematical functions needed to aggregate the values of the sub-nodes as well. These functions are called aggregation operators. The most commonly used aggregation operators are simple averaging functions, but in special cases other functions, like FISAO (Fuzzy Inference System-like Aggregation Operator), are also useful (Lilik et al., 2021).

4. FUZZY SIGNATURE OF MATERIAL HANDLING IN FUNCTIONAL PRODUCTION SYSTEMS

The problem was analyzed in the hall of a steel forging company. Its main product line is forged components for the automotive industry in medium sized batches. The area of the hall is around 12,000 m^2 and produces around 50 different types of finished goods. The activities performed in the plant are:

- Cutting the steel rods,
- Heating in an induction chamber
- Forging by semi-automatic forging machines,
- Grinding the burr from the semi-finished parts by manually operated hand grinders,
- Heat treatment in gas-heated chambers,
- Surface cleaning with sandblasting,
- Crack searching,
- Quality inspection, and packaging.

These activities are performed around 50 individual workstations in total. These are grouped in shops according to their technology and supplied by internal storage areas according to an individual schedule. The shops work separately and supply the storage area of the next shop. Since economical production batches are different according to the technology, there is a significant amount of semi-finished inventory in the storage areas. Taking into account the customer demands and economical production quantities, jobs of shops are scheduled backward, so "one piece flow" via the production process is not possible. Due to area constraints in the plant, there is no space for a buffer stock next to the machines, and just one cargo rack space is normally available for the raw material and one for the finished goods. Hence, cargo racks must be changed as they become empty or full within one cycle of the machine. Otherwise, the machine will stop due to the lack of raw materials or sufficient storage space.

Since the packs of some materials are heavier and the service of some machines requires small and agile forklifts, lighter and taller capacity forklifts have to be operated. Therefore, not all forklifts can perform all material handling tasks.

Operation areas are assigned to forklifts – sometimes to more than one shop –, where they have to "stay alert" to follow the progress of the production. These areas are defined by the management of the logistics department based on previous experience, so the workload of forklifts in theory is balanced. Since no remote signal system is installed, material handling tasks are performed when they are recognized by the forklift drivers. The work instructions for the forklift drivers are the following:

- be familiar with the progression of the production of the dedicated area;
- perform the material handling tasks as soon as possible;
- if there is more than one task at the same time, choose the task with the shortest processing time;
- if more machines stop working at the same time due to the lack of available material, the one with the highest priority list must be served first.

Since work instructions cannot provide adequate support to all situations, the final quality of service is mostly affected by the individual expertise and decisions of forklift drivers. The main disadvantage of this method of working is that there is no real-time overview of the tasks available. The same goes for the forklift drivers and the logistics management. Therefore, the forklift drivers have to make many personal and subjective, individual and uncontrolled decisions. As these decisions are taken in unknown circumstances, it is not possible to measure how the decisions approximate the mathematically available optimum. During our study it was assumed that a radio-based signal system was available, and all tasks were real time and visible for all forklift drivers. Henceforth, the order of tasks will be specified according to the work instruction presented above.

The reasons for production losses are systematically collected to help improve the efficiency of the plant. To get the loss in financial units, the capacity losses are multiplied by the operating costs of the current workplaces. The performance assessment of logistics department is based on the summarized production losses caused by the lack of material handling. Therefore, the main goal of the logistics department is to minimize this cost without increasing the operational costs of the logistics.

The fuzzy signature constructed in our study was developed based on the expertise of the company and the work instructions listed above. Priority is calculated for each task and the one with the highest value is selected for execution. After the task has been executed, time and location parameters are modified, and the calculation is performed again. This process is cyclically repeated.

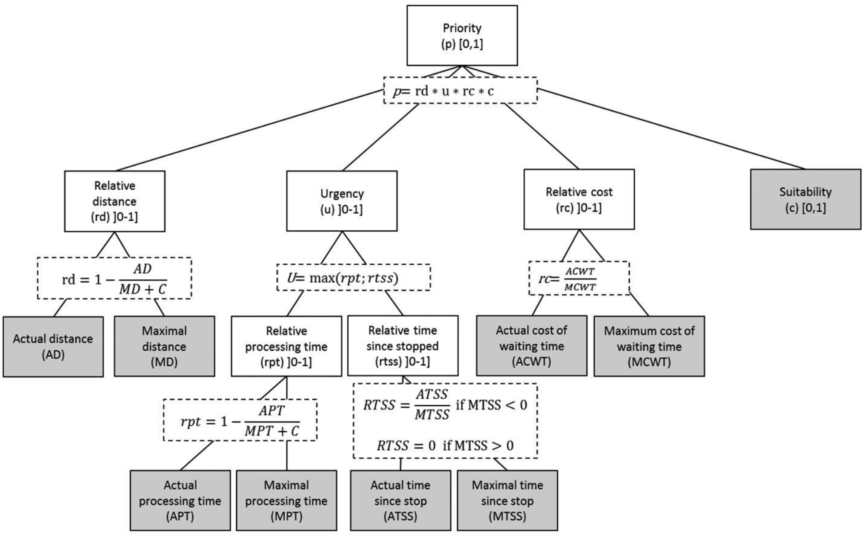
A hierarchical dependency tree of task prioritization processes was established. Priority (p) basically depends on distance, process time, urgency cost, and suitability of the forklift.

In the calculations, not these parameters but their modified versions are used, as follows:

- Relative distance (rd): The distance of the actual task divided by the biggest distance.
- Relative waiting cost (rc): The cost of the actual task divided by the highest cost.
- Relative urgency (u): This is calculated using the following parameters:
    - Relative processing time (rpt): The actual processing time divided by the lowest processing time.
    - Relative time since machine stopped (rtss): The machines that have stopped already are compared to one another. Time passed from the stoppage of the actual machine divided by the highest time since it was stopped.
- Suitability (c): One for forklifts that are able to perform the task and zero for the others.

A visualization of this dependency tree can be seen in Figure 2. This dependency structure can be used directly as a fuzzy signature, so it is complemented with the mathematical functions (in dashed line boxes) that implement the relations between the sub-nodes. Measured real number input parameters are denoted in squares with grey backgrounds. Values of the nodes in fuzzy signatures must lie between 0 and 1. This condition is satisfied by the aggregation functions applied here.

Figure 2 Visualization of the fuzzy signature dependency tree using aggregation functions



Source: Own compilation

5. NUMERICAL EXAMPLE AND RESULTS

The efficiency of the fuzzy signature presented in Sections 5 was tested and compared with results of an LP. Model, which was previously used in the same problem (Ferenczi et al., 2021). Ten different scenarios were created based on data of the investigated plant. Each scenario is a set of eight material handling tasks in actual production that have to be handled by the logistics. It is assumed that all tasks can be started immediately and no other task will arrive at the set during the performance. As an example the task and their parameters of the first scenarios can be seen in Table 1 (other tables contain data of the same scenario). The competency matrix of the forklifts is shown in Table 2. The travelling times between the tasks are shown in Table 3. The asymmetry of the matrix is due to one-way routes of the plant. The results of the first calculation cycle can be seen in Table 4, where task G2 was selected for execution.

Table 1 Parameters of the first scenario

Task ID	Deadline (min)	Processing time (min)	Waiting cost /min
G1	2	4	1,500
G2	4	1	6,000
G3	6	4	2,100
G4	7	2	4,300
G5	8	3	7,800
G6	9	3	1,200
G7	10	3	300
G8	11	3	950

Source: Our own compilation

Table 2 Competency matrix of the first scenario

Competency task ID/forklift	T1	T2
G1	1	0
G2	1	1
G3	0	1
G4	1	1
G5	1	1
G6	1	0
G7	0	1
G8	1	1

Source: Our own compilation

Table 3 Travelling time between the tasks

Travelling time from/to	G1	G2	G3	G4	G5	G6	G7	G8
Start	1	1	1	2	3	5	2	3
G1	0	3	4	4	3	1	5	5
G2	5	0	3	2	1	5	4	4
G3	1	3	0	1	3	1	2	1
G4	3	3	2	0	3	5	4	3
G5	4	2	2	3	0	5	2	3
G6	1	3	2	4	3	0	2	3
G7	1	5	3	3	4	2	0	5
G8	1	2	2	3	3	4	2	0

Source: Our own compilation

Table 4 Results of the first calculation cycle for the T1 forklift

Task ID	Relative distance (rd)	RPT	RTSS	Urgency (u)	Relative cost (rc)	Competency (c)	Priority (p)	Selected
G1	0.8	0.1	0	0.10	0.19	1	0.0160	
G2	0.8	0.75	0	0.75	0.77	1	0.4808	Y
G3	0.8	0.1	0	0.10	0.27	0	0.0000	
G4	0.7	0.5	0	0.50	0.55	1	0.1838	
G5	0.5	0.25	0	0.25	1.00	1	0.1250	
G6	0.2	0.25	0	0.25	0.15	1	0.0064	
G7	0.7	0.25	0	0.25	0.04	0	0.0000	
G8	0.5	0.25	0	0.25	0.12	1	0.0152	

Source: Own compilation

In Table 4, since there is idle stopped machine, RTSS is a constant 0. Tasks G3 and G7 cannot be performed due to zero suitability of the forklift. The highest priority is calculated to G2, so this task is selected for execution.

The results of all 10 test scenarios can be seen in Table 5. Since it has been proven that LP is an exact optimization method, results in the mathematical optimum of the total waiting cost of the optimal order that were calculated using the LP model were compared with the results of the fuzzy signature model. The above results based on fuzzy signature are approximately 41% higher than in case of LP. This means that the decision making with this signature does not attain the effectiveness of the LP model, but it is much easier to handle. The results of fuzzy signature based on the expert knowledge of the company, are more reliable than human decisions because the human factor has been removed from the process. Other aspects of the fuzzy signature approach compared to LP's and another computerized optimization algorithm are:

- Special knowledge needs: The fuzzy signature is based on basic calculations. No special knowledge is needed. In contrast, in the case of LP, the creation of the mathematical model and programming of the solver software requires special skills and expertise, especially when nonlinear phenomena have to be modeled, like the IF function.
- Transparency: The relationship of the sub values and the final value is readily understandable. In the case of LP, the calculations are not transparent, so applying this method can be confusing for users.
- Flexibility: If the circumstances change, the fuzzy signature can be easily modified even by local experts. In the case of LP it may require the complete redesign of the model.

Table 5 Results of comprehension of LP and fuzzy signature

Scenario	**1**	**2**	**3**	**4**	**5**	**6**
Total waiting cost (LP) HUF	237,000	234,000	243,000	239,000	230,000	201,000
Total waiting cost (Fuzzy) HUF	457,000	331,000	327,000	331,000	305,000	281,000
Deviation (%)	92.8%	41.5%	34.6%	38.5%	32.6%	39.8%
Scenario	6	7	8	9	10	Average deviation (%)
Total waiting cost (LP) HUF	201,000	242,000	203,000	240,000	215,000	
Total waiting cost (Fuzzy) HUF	281,000	322,000	293,000	326,000	257,000	
Deviation (%)	39.8%	33.1%	44.3%	35.8%	19.5%	41.3%

Source: Own compilation

6. CONCLUSIONS

In this paper a new approach of material handling management in functional production systems was presented. The evolutionary levels of automation were listed and examined. Although, total automation of material handling is technically possible, it has very high requirements and costs. To keep the costs low and increase the efficiency, as an intermediate level of the evolution, we proposed a novel fuzzy signature-based model that supports automatized decision making. In using this, the possible mistakes of human decisions are removed from the process, thus resulting in higher efficiency and coherent outcomes. The result was compared to the optimum given by an LP model. It was found that the fuzzy signature-based results are significantly different from the optimum, but they are still more reliable than haphazard human decisions. Further advantages of the fuzzy signature based optimization approach are its simplicity and that it does not require special knowledge of the system to understand and maintain it. Therefore, it can be implemented and widely used by small and medium-sized companies. These advantages, mainly from a human point of view, can help offset the lower economic results. The automated decision-making increases efficiency and reduces the stress load on employees.

In the near future we will study other mathematical functions for the aggregation and we will try to use different weights for different nodes in order to achieve greater efficiency.

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