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A NEW MODEL OF HUMAN RESOURCE MANAGEMENT FOR WORK IN AN INTENSIVE ENVIRONMENT

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Abstract
Managing operators is an important issue, especially in work-intensive environments and companies with hundreds or thousands of employees. The challenge of optimizing skilled labour selection on the production line, using measurable indicators and supported by highly sophisticated models and software solutions, is a significant global research topic.

In this manuscript, authors present a novel model for managing human operators based on a matrix of selected indicators. This model aims to enhance the planning, selection, and deployment of human resources. By optimizing the allocation of human resources to different workstations while utilizing available resources, the model facilitates monitoring and supervision of employee qualifications. To implement this model, a software solution designed for advanced labour optimization has been introduced. This software utilizes simulation and testing of various scenarios, which is increasingly crucial in intensive working environments.
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Key Words: Human Resource Management, Intensive Environment, Simulation Model, Business Indicator

1. INTRODUCTION

Human Resource Management (HRM) [1] is an important issue that has been addressed from various perspectives. It has emerging importance, particularly in work-intensive environments and in companies with hundreds or thousands of employees [2]. On the other hand, intensive work environments [3] are characterized by demanding high levels of output, performance, and productivity within limited timeframes. These environments [4] can be found in various industries, including healthcare, manufacturing, emergency services, and transportation, among others. Conversely, a perpetual goal is the reduction of costs and the achievement of some Lean principles [5]. Intensive work environments can be physically and mentally demanding, often requiring employees to work long hours under high-pressure situations [6]. The challenge of optimally managing human resources, based on measurable indicators and supported by highly sophisticated models and software solutions, is a significant global research topic.

HRM plays a critical role in ensuring that employees within intensive work environments are recruited, trained, and supported in manners that foster their well-being, performance, and retention [7, 8]. There are additional compelling reasons why HRM is essential in such contexts [9], including: Recruitment and Selection; Training and Development [10]: Health and Safety; Employee Motivation and Employee Retention. Ultimately, determining the most effective HRM model for an intensive work environment depends on a range of factors, including the organization's objectives, the nature of the work performed, the workforce's skills and capabilities, and HRM costs [11]. Various tools have been employed to address the HRM challenges within such environments [12, 13]. Notably, the individual work performance model has been recognized as a crucial consideration [14], along with the interplay between performance and skills and knowledge.

Furthermore, the development of models and prototypes for innovative tools that facilitate a clear visualization of employee competencies, including identifying areas for improvement (employee gaps), while also accommodating their preferences, is highlighted as a significant issue [15]. This emphasis on innovative tools reflects the ongoing pursuit of enhancing HRM practices in intensive work environments.

A skill matrix tool is utilized by organizations to identify the skills and knowledge necessary for each role within the organization. It serves to assess the current skills and knowledge possessed by employees and to pinpoint any gaps that require addressing [16]. Research reports [17, 18] indicate that the majority of companies acknowledge the significance of forecasting human resources, implementing systematic employee promotion, utilizing skill matrices, maximizing the productivity of existing manpower, and optimizing human resource utilization. Typically, a skill matrix outlines a matrix structure with employees' names along one axis and the required skills or competencies along the other [19]. This tool serves to monitor employees' developmental progress and to highlight areas where training is needed. Additionally, the skill matrix tool is instrumental in supporting succession planning and talent management within the organization. The skill matrix encompasses diverse skill items that the organization requires (with skill levels graded from 1 to 10 for each item, where 1 denotes the lowest and 10 the highest proficiency) [20]. Key indicators within a skill matrix usually include [21]: Competencies, Job Roles, Skill Levels, Training Needs, Employee Performance, Succession Planning, Recruitment, Performance Management, Workforce Planning, and Employee Engagement.

The challenge of solving Human Resource Management (HRM) problems, such as deciding which employees are best suited for specific projects, can be effectively addressed using fuzzy sets and neural networks [22], a significant aspect within the context of Industry 4.0 [1]. Some researchers have proposed dynamic skill matrices based on machine learning algorithms [23], indicating the potential to integrate fuzzy logic for defining weight factors within skill matrices.

In this study, the authors introduce a novel HRM model built upon an enhanced skill matrix tool. This model incorporates new indicators to enhance the planning, selection, and allocation of human resources. By introducing new indicators and corresponding weight factors, the authors have developed a model that optimizes the deployment of human resources across various workstations. This optimization leverages available resources while concurrently facilitating the oversight of employee qualifications. Additionally, the model integrates the implementation of necessary learning and training programs. The determination of these factors and their relative importance is achieved through a combination of Delphi analysis and fuzzy logic. Within the framework of this developed model, the authors present a software solution that not only enables advanced HRM practices but also allows for the simulation and testing of diverse scenarios. This capability is particularly important within intensive working environments. The practical implementation of the developed model and software in various companies has provided direct evidence of success. The measurement of business indicators, including nonconformities, training costs, equipment utilization levels, reclamation numbers, and overall system efficiency, attests to the model's efficacy. Moreover, the developed software serves as a valuable simulation tool for effective HRM practices.

2. DEVELOPMENT OF NEW MODEL OF SKILL MATRIX

The qualification matrix represents a set of data for the combination of employee-operation/machine/product, which defines who can perform which operation and with what level of proficiency [24]. This research identifies 12 parameters that are important for the process of creating and managing the qualification matrix, and therefore important for business improvement. The parameters that define the matrix can be classified into four categories (Table I): Creating the matrix; Updating the matrix; Applying data from the matrix; and Results of applying the matrix.

Table I: Categories and parameters of the qualification matrix.

Creating the matrix		**Updating the matrix**			**Applying data**			**Results of applying the matrix**			
Training levels	Formation of the matrix	Influential factors	Frequency of updates	Evaluation method of employees	Scheduling workforce according to the matrix	Creation of training plans	Creation of inspection/examination plans	Improvement of organizational performance	Increase organizational flexibility	Enhance product quality	Ability to track overall skill factor per employee

As a contribution of this work in relation to existing solutions, the introduction of the concepts of operation weight factor and overall operator training factor stands out. The introduction of these factors enables the determination of priorities in the process of allocating personnel based on operations and their corresponding work tasks. The factor of product weight – operation (T) is determined using the Delphi method and is defined based on four factors that describe the manufacturing process of the product (Table II), which are: the ratio of cycle time per person/product-operation – factor A; the number of components integrated into the product assembly – factor B; the required number of steps for product finalization – factor V; the visual coefficient (product quality) – factor G; and the factor of operation weight – Delphi method.

Table II: Factors of the product T manufacturing process.

Operation	**Cycle time**	**Operator working time**	**Factor A**	**Number of components for installation**	**Factor B**	**Number of steps in the standard operation**	**Factor V**	**Factor G**	**Weight of the product T**
Operation 1	43	38	0.88	4	0	4	0.5	0.5	1.88
Operation 2	35	30	0.86	2	0	10	1	0.5	2.36
Operation 3	49	47	0.96	2	0	12	1	0	1.96
Operation 4	48	48	1	8	0.5	6	1	0.5	3.00
Operation 5	27	22	0.81	19	1	2	0	1	2.81
Operation 6	32	32	1	26	1	7	1	1	4.00
Operation 7	60	45	0.75	6	0.5	2	0	0	1.25

Factor A is determined by the ratio of the cycle time prescribed for product manufacturing and the time required for the operator to perform the final processing of that product. This factor represents the level of operator workload. The other factors (B, V, and G), with their relative importance values assigned to them are defined through the application of Delphi analysis and fuzzy logic. By combining the Delphi method with fuzzy logic, the decision-making process can benefit from the aggregation of expert opinions while also capturing the vagueness and uncertainty associated with the experts' knowledge. Fuzzy logic has been used to aggregate the fuzzy opinions of the experts and derive a consensus or decision based on the degrees of membership assigned to different possibilities. Authors of this paper combined the Delphi method to select a panel of experts, such as top managers, quality managers, and production managers. Also, a questionnaire asking the experts to rate the importance of different factors influencing manufacturing process, such as number of components integrated into the product assembly, required number of steps for product finalization, and the visual coefficient (product quality) has been prepared. Experts, comprising engineers of various profiles employed in tasks being evaluated, with relevant experience (more than 5 years), as well as technicians from the process with equal or greater work experience, assign the defined values (0, 0.5, and 1) to process values for each of the factors (number of components being installed in the product, number of steps involved in product manufacturing, required final quality of the product). The rating scale has been numerical, ranging from 1-5, where 1 denotes insignificant importance and 5 represents highly significant importance. The ratings obtained from the Delphi method were converted into fuzzy linguistic terms. Membership functions to each fuzzy linguistic term were assigned. These functions defined the degree of membership for each factor in different linguistic terms. The fuzzy ratings from all the experts were combined using appropriate average fuzzy logic operations on the aggregation method defined by Chang [25]. Normalisation has been performed on the combined fuzzy ratings in order to obtain weights. This normalization process ensures that the weights sum up to 1. The normalized weights were applied to the factors influencing manufacturing process to determine their relative importance. The results were summarized to provide feedback to the experts, showing the average ratings and any comments or insights from other participants. Multiple rounds of questionnaires, allowing the experts to revise their ratings based on the feedback and discussion in each round were performed. The process has been repeated until a consensus was reached. Finally, the values: 0, 0.5, and 1 is ensured through expert analysis using previously defined questionnaires (Table II), which are unique to this study.

The distribution of operators across workstations should be such that work efficiency is significantly increased. It is important to consider the growing level of training and strive for the highest possible overall training index. The possibility of human error due to inadequate training should be minimized as much as possible. Naturally, the intention is to have personnel capable of handling a greater number of different activities (products). There is currently no known mechanism (tool) in the market for distributing workforce across workstations in line with their levels of capability and for monitoring the effects of this process.

The offered new model and software based on it integrate all influential factors for defining automated workforce management. Trends in achieving and preserving the capabilities of each individual to perform a specific job are monitored, with the condition of increasing work efficiency and effectiveness. In this case, the production process can be organized based on available competent personnel. The implementation of the new model enables the creation of short-term and long-term workforce preparation plans based on real data on training, actual production plans, and real job requirements. Automating this process contributes to better and more efficient tracking of operator development. Additionally, it eliminates the subjective bias of immediate supervisors in workforce allocation. Its workflow logic is based on an algorithm created from a set of rules and constraints and consists of three components: Input data, Logic part, and Output data.

2.1 Input data

The input data, which serve as parameters for the database and decision-making, include the following: List of operators, Training levels of operators, Product-operation codebook, Product assemblies (cycle times, number of operators required, weighting factors for each operation, specific to each product), Assignment of operators to shifts and production units, List of production units, List of machines, List of complaints, List of process checks, and Attendance records.

2.2 Business logic

This segment performs the following tasks in addition to creating correlations between input data: (1) Suggesting an optimal allocation of operators to workstations. (2) Creating long-term production plans. (3) Automatically adjusting the training levels. (4) Creating practice plans.

The relationship between the training matrix (Table II) and the production plan can be mathematically represented as follows:

$$\begin{bmatrix} a_{11}a_{12} \dots \dots a_{1j} \dots \dots a_{1n} \\ a_{21}a_{22} \dots \dots a_{1j} \dots \dots a_{2n} \\ \dots \dots \dots \dots \dots \dots \dots \dots \dots . . \\ a_{i1}a_{i2} \dots \dots a_{ij} \dots \dots a_{in} \\ \dots \dots \dots \dots \dots \dots \dots \dots \dots . . \\ \dots \dots \dots \dots \dots \dots \dots \dots \dots . . \\ a_{l1}a_{l2} \dots \dots a_{lj} \dots \dots a_{ln} \end{bmatrix} \begin{Bmatrix} X_1 \\ X_2 \\ . \\ . \\ X_j \\ . \\ . \\ X_m \end{Bmatrix} = \begin{Bmatrix} b_1 \\ b_2 \\ . \\ . \\ b_j \\ . \\ . \\ b_n \end{Bmatrix} \tag{1}$$

where:

- a_{ij} – training parameter,
- i – number of employed operators, $i = 1, 2, \dots, n$, refers to the number of employees in direct positions, i.e., positions related to operational work in the implementation of a specific operation,
- j – operator qualifications, $j = 1, 2, 3, 4$, defined in four levels,
- X_i – number of different operations, $i = 1, 2, \dots, m$, and
- b_i – number of production lines from the production plan, $i = 1, 2, \dots, m$.

This can also be represented in the form of a system of equations:

$$\begin{array}{c} a_{11}X_1 + a_{12}X_2 + \cdots \dots + a_{1j}X_j + \cdots \dots + a_{1n}X_n = b_1 \\ a_{21}X_1 + a_{22}X_2 + \cdots \dots + a_{2j}X_j + \cdots \dots + a_{2n}X_n = b_2 \\ \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . . \\ a_{j1}X_1 + a_{j2}X_2 + \cdots \dots + a_{jj}X_j + \cdots \dots + a_{jn}X_n = b_j \\ \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . . \\ \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . . \\ a_{l1}X_1 + a_{l2}X_2 + \cdots \dots + a_{lj}X_j + \cdots \dots + a_{ln}X_n = b_l \\ a_{m1}X_1 + a_{m2}X_2 + \cdots + a_{mj}X_j + \cdots + a_{mn}X_n = b_m \end{array} \tag{2}$$

Or:

$$\sum_{j=1}^{n} a_{ij}X_j = b_i, \ i = 1, 2, \dots, m \tag{3}$$

Automatic adjustment of training levels is necessary and a continuous activity (at every moment) because the influential factors vary at different moments:

$$a_{ij} = f(y_i, z_i, x_i) \tag{4}$$

where: y_i – elapsed time since the last work on the operation, z_i – assessment of the check, and x_i – quality control.

2.3 Output data

The output data from the software consists of: (1) Presence of operators for the selected period. (2) Updated list of operators with their training levels in real-time. (3) Movement of training levels per operator/product for the selected period. (4) Results of work checks per product/operator for the selected period. (5) Efficiency of utilization of available workforce. (6) Number of errors per operator/product for the selected period. (7) Rotation of operators across products for a specified period. (8) Training plan for operators to populate the matrix and satisfy the conditions. (9) Training implementation report. (10) Process check implementation report. (11) Report on the implementation of defined corrective measures.

All the mentioned reports are intended to serve for additional analysis of the work force engagement process in order to improve the process itself and standardize the quality of work across all available workforce by equalizing the levels of proficiency.

The procedure for automatic scheduling of operators at workstations allows operators to be automatically assigned to workstations/products in any work-intensive environment. The procedure enables the complete elimination of human influence in this process, thereby eliminating any subjectivity. The expected result is the most efficient schedule in terms of achieving maximum work efficiency while minimizing the possibility of errors occurring during work.

3. SOFTWARE SOLUTION AND SIMULATION

3.1 Architecture and functionalities of simulation software – Forceman Commander

Typically, a three-tier structure is employed for developing general web application components and defining their interconnections. This structure comprises the front-end, back-end, and database tier. The front-end tier, situated at the topmost level, manages the user interface, processes client requests, and presents comprehensible outcomes. Contemporary development practices often incorporate JavaScript scripting language, its frameworks, or alternative frameworks rooted in programming languages such as PHP, Java, and Ruby for implementation of the front-end tier in web client part of the application. Interaction with other tiers is facilitated through API calls.

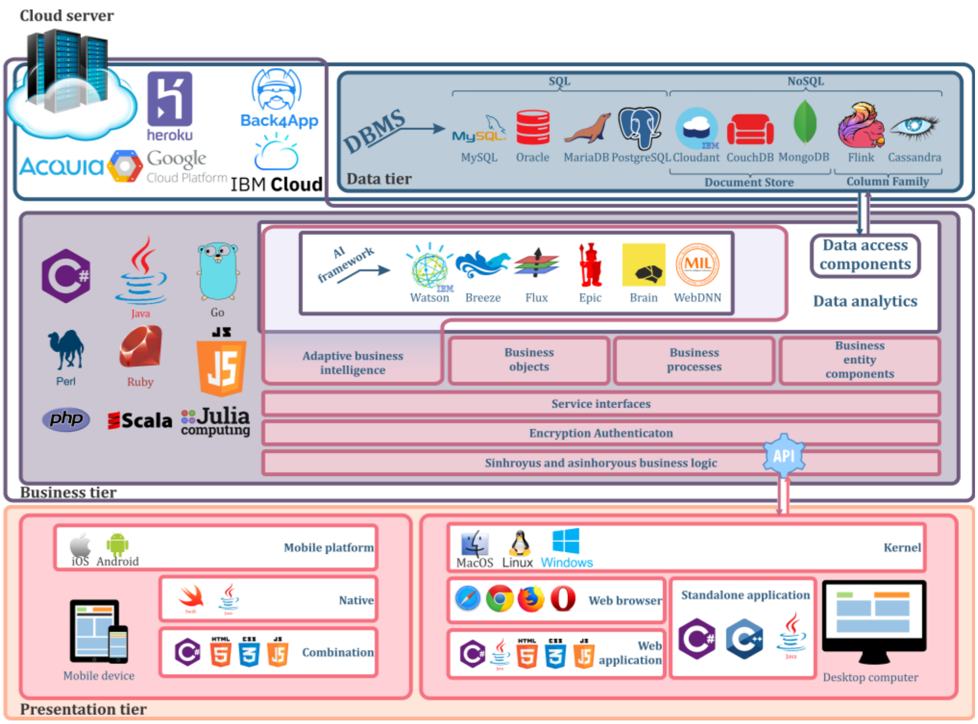


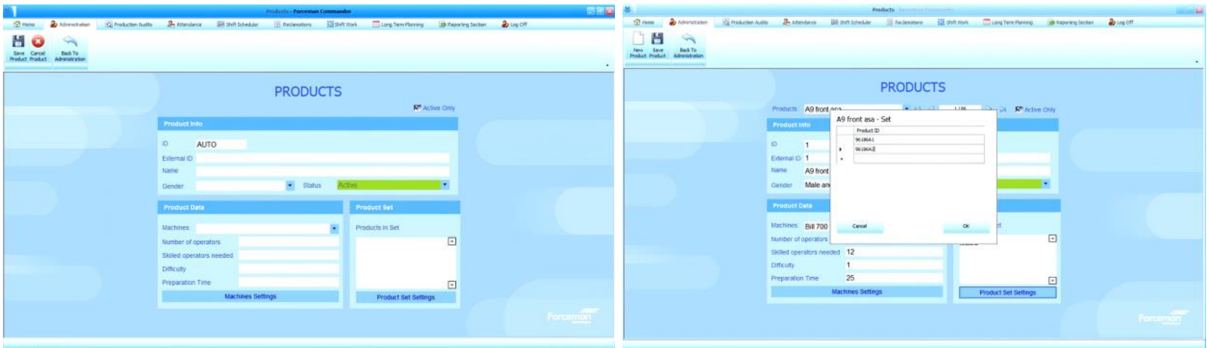
Figure 1: Digital engineering for productivity improvement.

The backend tier may be hosted either on on-premises servers or a distributed cloud server, determined by the processing power demands of the entire software solution. The data access tier enables the retrieval of data within the software solution's confines or from data accessible through external cloud service providers.

Moreover, altering the data storage technology, including various database management systems, can be done with minimal impact on the business logic. The organization of components into flexible tiers offers numerous benefits, including enhanced modularity, simplified management and maintenance of individual components, autonomy between technologies and stacks employed in diverse tiers, and a distinct backend tier enabling the deployment of various databases. This flexibility enables scalability and the addition of multiple web servers to accommodate the future growth of small and medium enterprises, resulting in the development of decentralized applications (Fig. 1). Based on this facts and the research model the software solution is developed as multitier web application based on JavaScript technologies including React framework for presentation tier, Node.js and Express.js for application tier, and MongoDB for NoSQL databases data tier. In addition, the Forceman Commander is registered software solution.

The software has the following modules with accompanied activities:

1. **Home:** Module has 4 basic functionalities: Attendance, Shift Work, Production Audits and Log off.
2. **Administration:** By accessing the Administration tab, a list is opened that contains all the elements that enable the administration of the database. These include: Workers, Units, Machine, Products (Fig. 2), Buyers, Audit Checklist and Settings.



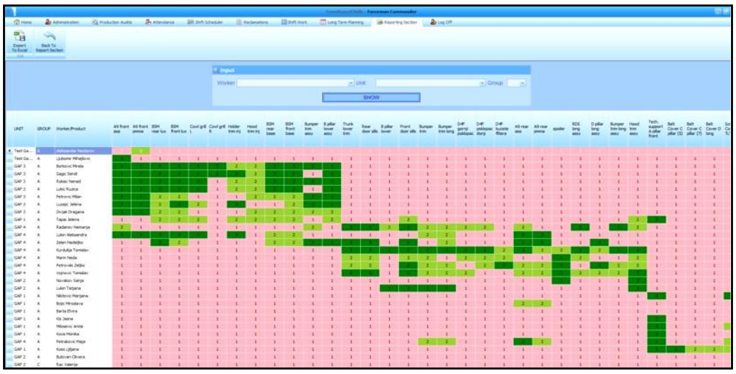
Display screen for creating a new product | The display screen for creating a machine-product link

Figure 2: Software solution user interfaces for creation of new products and machine-product lines.

3. **Production Audits:** To define a new audit, the following data needs to be entered: Document number, Workers, Products, Result, and Note.
4. **Attendance:** By pressing the Attendance tab on the home screen, a sub-form opens with 2 buttons for entering attendance data: (1) Daily/Shift Level Attendance (Attendance): this button allows entering attendance information on a daily or shift basis. (2) Attendance Scheduler for Longer Time Periods with Absence Reason (Attendance scheduler): this button enables entering attendance data for an extended time period along with the reason for absence.
5. **Definition of shift schedule (Shift Scheduler):** By pressing the Shift Scheduler tab, a form for entering the shift schedule by weeks opens. On the displayed form, enter the following data: (1) Week: Enter the week number within the year for which the shift schedule is being created. (2) Year: Enter the calendar year for which the shift schedule is being created. (3) Workdays per Week: Tick the checkboxes next to the day names to indicate the working days in the week. (4) Shift Assignment: Assign a shift number (1, 2, and 3) to each day according to the shift rotation sequence.
6. **For reclamations (Reclamations):** By pressing the Administration tab and then the Reclamation button, a form opens for searching and modifying data about entered machines. To review the entered data, you can use the form by entering the reclamation number or using the arrows on the right side to search page by page.
7. **Planning of shifts (Shift Work):** After completing the operator's attendance login, you can proceed to create a shift work schedule by pressing the Shift Work button. The module

covers, Production Plan (Fig. 3), Graphs, Placements, Training, Audit Plan and Long Term Planning.

The display screen showing all registered machines



Display screen with ratings from the training level

Figure 3: Software solution user interfaces to display all registered machines and ratings from the training level.

8. **Reporting Section:** This section contains reports generated based on the data obtained from end users through four displayed forms: Attendance, Shift work, Production Audit and Reclamations. By activating the Reports tab (Reporting section), a form opens where you can select the desired reports: Revisions report, Shift scheduler, Audits report, Audit plan, Corrective actions, Skills report (Fig. 3), Worker skill, Worker scheduler, Training plan and Training report.
9. **Simulation Section:** Based on previously uploaded data system could make simulation or prediction. Users could set initiate data and make analysis of different scenarios that could happen in 6 months, 12 or 24 months span. In addition system could provide the suggestion which indicators should be improved or corrected in order to have the most effective transition from present state to the desired state.

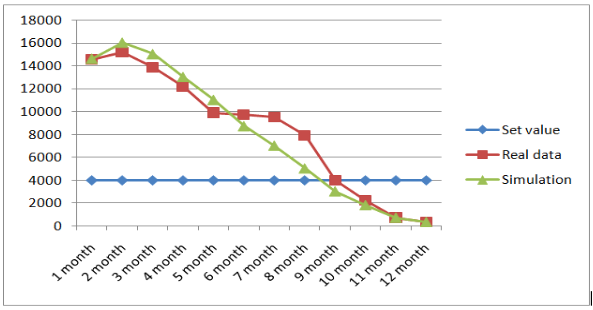
Complete solution is intuitive and could be used in network environment. In addition the most important feature is possibility of the system to learn based on real data.

3.2 Case study and simulation results

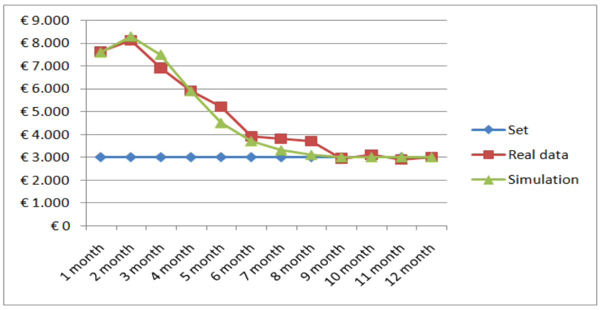
The final version of the Model has practical confirmation and direct implementation in several foreign and domestic companies. The complete project of testing the software solution lasted for 12 months and involved eight companies. The businesses of the mentioned companies are in the automotive industry, pharmaceutical industry, construction industry, metal processing industry, heating equipment production, and consumer goods manufacturing. Total number of companies were eight and in this paper, the case study from one company is presented.

Presented model and software present a completely new and more comprehensive approach to personnel planning, training, classification, and deployment. In order to prove the validity of the model it was important on one hand to provide analysis on the real life data in order to monitor how the company will be reached stated objective and in the other hand to test simulation module.

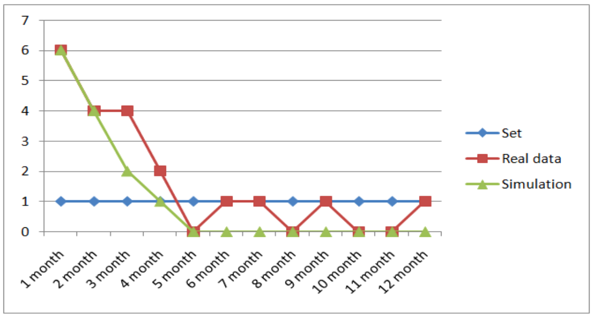
The results are presented through original diagrams (Fig. 4) and table (Table III) with real data on: a) Number of defective pieces per million (ppm): this parameter represents the count of defective items per one million units produced; b) Training costs: this parameter refers to the expenses associated with training programs; c) Number of customer complaints: this parameter indicates the count of complaints received from customers; d) Equipment utilization: this parameter measures the efficiency of equipment usage; e) Overall work efficiency: this parameter provides an assessment of the overall effectiveness and productivity of work.



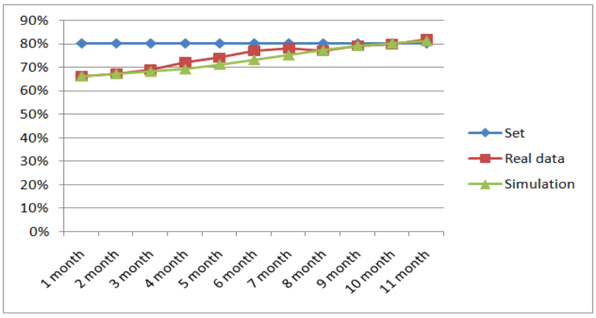
a) Defective pieces per million



b) Training costs



c) Number of customer complains



d) Equipment performances

Figure 4: Diagrams for the company that participated in the Case study.

The presented diagrams have 3 different graphs: simulation curve, real life data and value that was set as objective. The simulation was set using data from initial state, according to business logic of application the software gave simulation curve that depicts prediction of the system (for example how the number of nonconformities will decrease during the time, reaching set objective).

Table III: Scheduled starting and finishing times of activities.

Company that participated in Case study (12 months)		**Plan**				
		a) Defective pieces [unit]	**b) Training costs** [€]	**c) Equipment utilization** [%]	**d) Number of customer complaints**	**e) Overall work efficiency** [%]
		4000	3000	85	1	90
Initial state		14600	7600	66	6	74
New state		320	2600	85	1	90
Improvements [%] according to:	Plan	92	13.3	0	0	0
	Initial state	97.8	65.8	28.8	83.3	21.6

In order to achieve this goal the system has data about all workers and processes. By intervening in training (continuous monitoring and retraining), improving the allocation of employees to workstations, and eliminating unnecessary personnel from the production lines, the company was able to ensure a high-quality workforce and reduce costs. After the simulation part 8 companies that participated in experiment provided needed actions according to simulation report, and data were gathered. After the experiment, it was possible to conclude: 1) By comparing the initial state with the achieved results, positive outcomes have been realized among all mentioned users of the new Model across various segments. The percentage values of improvements differ depending on the initial state encountered. 2) Simulation software gave excellent prediction (Fig. 4) in all 8 examined studies.

Overall, business performance in all examples is positive and improved. When comparing the achieved results with the plan, it is evident that there is improvement, although not complete in certain segments. The reasons for this can be attributed to the short implementation time of the Model and the very poor initial state.

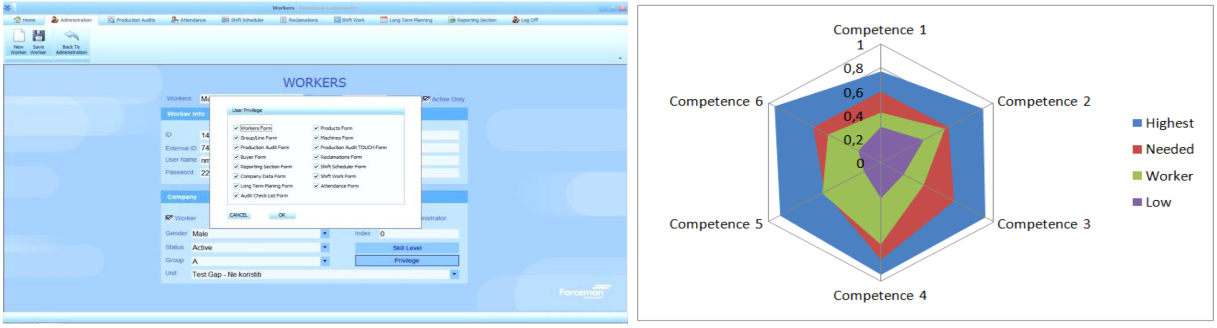


Figure 5: Analysis and development of competences for an individual worker.

The defect rate and training segment clearly indicate a problem with an incompetent workforce. The level of training and the allocation of individuals to specific positions were not adequate. The qualification matrix revealed the following (Fig. 5): The number of available operators; The level of their training; The number of trained operators for each position; The number of inadequately trained operators; The number of unassigned operators at a given time; and The number of operators who were underutilized or not engaged for an extended period. These insights from the qualification matrix shed light on the issues related to workforce competence and allocation, which contributed to the high defect rate and highlighted the need for improved training and personnel management strategies.

As the Model operates with real and comprehensive data about each employee, the management had access to a report containing the names of operators who were competent and those who were not or were underperforming. This resulted in positive outcomes within a short period, including: Reduction in defect rates; Decrease in training costs; Improved equipment utilization; Decrease in customer complaints and Enhancement of overall efficiency.

4. CONCLUSION

In this manuscript, authors presented the new model of HRM for work in an intensive environment. In order to improve HRM authors of this paper started from skill matrix tool to identify the skills and knowledge required for each role in the organization, assess the current skills and knowledge of employees, and identify gaps that need to be filled indicators and finally assign the best-qualified workers for specific processes, activities and operation. The new model introduced the 12 indicators as well as concept of using fuzzy and Delphi in definition of influential factors. Complete workflow logic is based on an algorithm created from a set of rules and constraints and consists of three components: Input data, Logic part, and Output data. The algorithm and mathematical model are presented and discussed.

The characteristics of the new model are as following: Up-to-date matrix with levels of training; Optimization of training; Determination of the work performance of each operator; Ability to create realistic training; Monitoring the implementation of training and practice sessions; Ability to rank operators; Applicability at all levels of management; Independent monitoring of the implementation of checks; Calculation of maximum efficiency and selection of operators for each workstation; Allocation of workforce at the beginning of a shift; Ability to reorganize and adapt the workforce to unforeseen situations; Capability to carry out sudden interventions in a very short time; Ability to generate a large number of reports and Ability to visually display workforce utilization, such as through Gantt charts.

Based on the presented model the complete software solution (Forceman Commander) is presented. The operational functionality of the Forceman Commander Software package is fully aligned with the requirements. This solution had been tested in 8 different companies. The case study presented in this manuscript (Fig. 4 and Table III) clearly demonstrate all advantages of model and software solution. The software is consisted of nine different modules including the full reporting and simulation module. The simulation module is especially important because it enables possibility of setting and analysing different scenarios in the companies. In addition, this module enables possibility to focus on the critical indicators and factors giving possibilities to improve each of that, find the target ones and analyse different scenarios. The direction of future research will be focus on development of more robust simulation model and improvement of business logic of the software. In addition, more data from different companies will enable creating knowledge database in order to provide suggestions and support for decision-making.

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