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OPTIMISATION OF DECISION-MAKING PROCESS IN INDUSTRIAL ROBOT SELECTION

The successful selection process of industrial robots (IRs) for today's Cyber-Physical Systems is an important topic and there are different possibilities to solve the task. The primary task is to estimate the existing IR selection systems according to the suitability analysis and to highlight the main positive features and problematic areas. The objective of the reverse task is to carry out the sensitivity analysis of the existing robot-based manufacturing systems. The matching of these two approaches helps decision makers to develop the main principles of IR selection in today`s multidimensional and fast-changing economic world.

1. INTRODUCTION

The importance of industrial robots (IRs) in manufacturing is increasing continuously. This is caused by their flexibility, productivity, relatively low cost and large technological capabilities. The nomenclature and functionality of modern IRs are remarkable. IRs are also basic components of Cyber-Physical Systems (CPS), which, at the same time, form an important part of Industry 4.0 [1]. Due to their large variety and application possibilities, the selection of a most suitable IR is a complicated task. Several selection criteria need to be taken into consideration. The challenge of choosing a suitable robot for a certain manufacturing application lays often not only in knowing whether a robot is needed but in predicting what tasks are the most suitable for the current application. It is also necessary to consider that today's IRs are becoming smarter, faster, and more and more adaptable and collaborative.

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2. ROBOT-BASED MANUFACTURING CELL

A robot-based manufacturing cell (system) can be considered as a closed system within a larger unit (workshop). The system can be described with the help of dimensioning its main parts, giving the relations between the parts, and forming the structure of the system. These relations are workpiece loading-unloading equipment, gripper (end effector), IR working area, range, loading capacity, controlled coordinates of IR and MT, etc.

A study was performed at the end of 2017 to determine the utilization of robot-based manufacturing cell´s in Estonian industry. The goal of the study was to compare production cell design objectives to achieved KPI´s. The study was carried out by interviewing executives from different company management levels (production managers, R&D engineers and setup technicians), gathering data from implemented MES system, where it was available and mapping the cells layout with technological capabilities. Altogether 14 robot based manufacturing cell´s where investigated of which a majority 64% where welding, 22% CNC machine tending and 14% material handling cell´s. The first cell was implemented at 2008 and the last one implementation process where ongoing. The total investment between 50k to 450k EUR, inflation not taken in to account.

Information was gathered in four main fields: company profile and strategy, cell layout and equipment, manufactured products and process data and shortcomings or improvement necessary to perform. From that data, a preliminary report was made which evaluated the production cells performance values and economical aspects.

Performance was assessed through following parameters setup, cycle, operational, rework and maintenance times, operators needed, lots size and repeatability, total number of setup products at the cell. Throughput, cell utilization and OEE was calculated and compared with cell design goals.

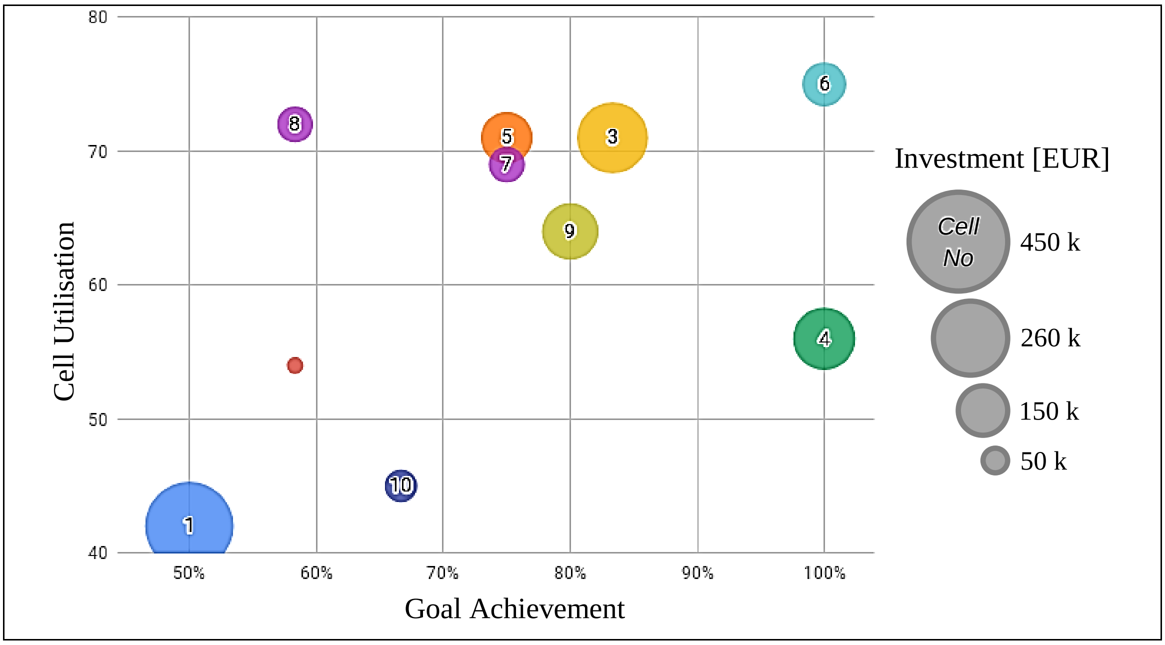

Fig. 1. Production cell design goal fulfilment

Economical input parameters where chosen that best described the goals set by the company or department management. Parameters included among others where net income, net operating profit, cost per hour, discounted payback period. As a result goal achievement analysis [2] where performed, where cell utilization, investment value and overall goal fulfilment where mapped (see Fig. 1) and compared. Production cell design objectives where once again assessed.

As a second step, a wider analysis where performed to assess production cell intelligent level and automation or engineering level by the categorical framework of manufacturing [3]. This analysis shows the production cells current state, compared to global manufacturing trends (see Fig. 2) and can lead to steps needed to perform for improve manufacturing and leap to Industry 4.0 principals.

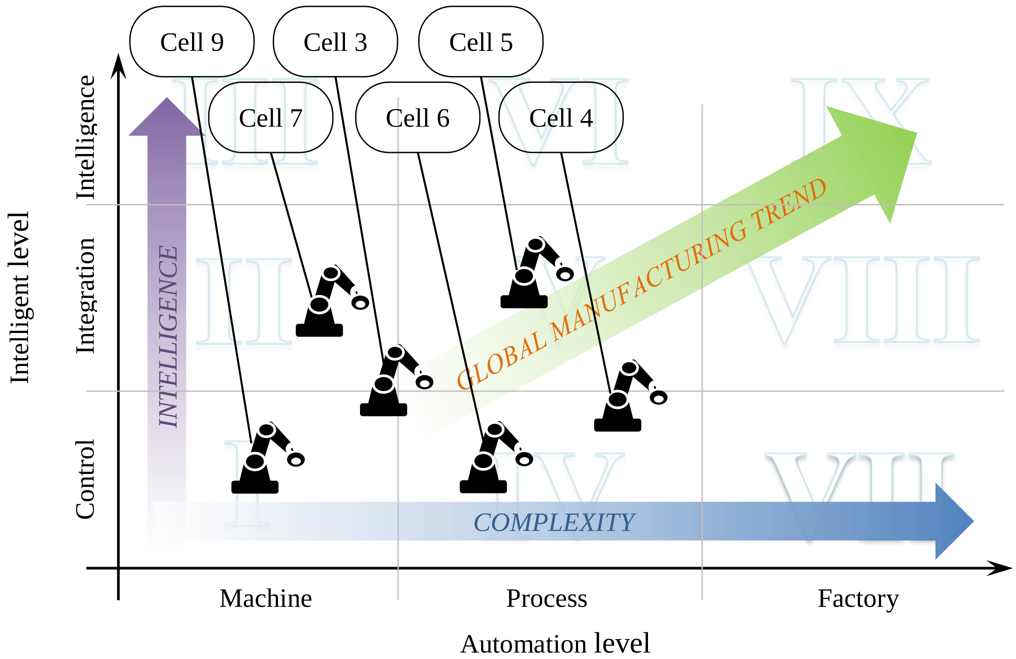

Fig. 2. Production cells state on manufacturing categorical framework

Based on this generalization, it is possible to develop a set of industrial robot selection principals and rules which best suits regional industry level. Furthermore, gathering different production cell development approaches from industry and judging their accuracy is a vital input for developing robot selection workflow. This can be used as an expert advice in the decision-making process.

3. DECISION-MAKING TASK FOR ROBOT-CELL COMPONENT SELECTION

The decision-making problems have been treated individually, consistency is not kept between the decision-making functions regarding the assumptions and data structures. These isolated decision-making stages do not help to achieve the global optimum solution because the decision-making problems in manufacturing involve very complex data processing. The elementary estimations are very strongly dependent on each other and the real technological resources (capabilities) must be taken into consideration. Therefore, rational decisions usually cannot be made simply with sequential procedures. However, with modelling and simulation procedures, it is possible to analyse the alternatives and find the best solution. The other possibility is to start from the complex systems theory [4, 5] and to develop a solution system architecture, allowing the reduction of complexity of a design process, minimizing risks in production system planning and enabling analysis of various production variants. For a better understanding of the whole complexity of the problem setup, it is useful to see the wider picture based on the ontology model (see Fig. 3) [6]. This shows the task positioning in the field of manufacturing in its whole complexity.

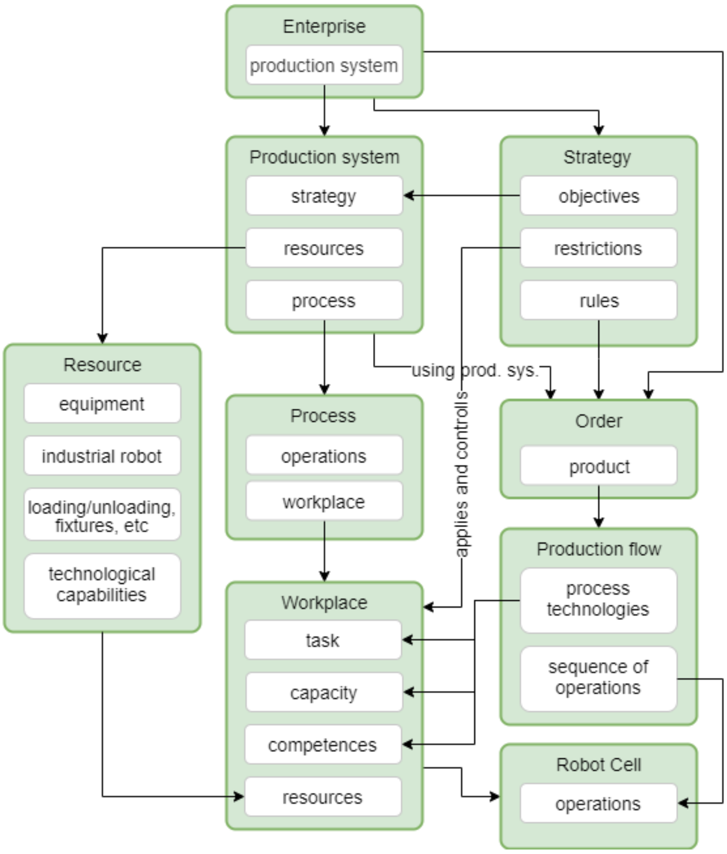

Fig. 3. Robot Cell Utilisation Ontology Model

The efficiency of manufacturing depends on how suitable the manufacturing system is for fulfilling of the company's strategy and how completely the product portfolio fits the technological capabilities of the manufacturing system, but also of course on how efficiently the company is using their resources and how productive they are in fulfilling orders. The results depend directly on the quality of decision-making process. Nowadays in manufacturing, decision support system (DSS) are used for complicated tasks. DSS [7] is a computer-based information system that supports business or organizational decision-making activities, typically resulting in ranking, sorting or choosing from among alternatives.

DSS's serve the management, operations, and planning levels of an organization (usually mid- and higher management) and help people make decisions about problems that may be rapidly changing and not easily specified in advance – i.e. unstructured and semi-structured decision problems. Decision support systems can be either fully computerized, human-powered or a combination of both. While academics have perceived DSS as a tool to support the decision-making process, DSS users see DSS as a tool to facilitate organizational processes that might support decision making. DSS is defined as follows:

1. DSS tends to be aimed at the less well structured, underspecified problem that upper-level managers typically face;
2. DSS attempts to combine the use of models or analytic techniques with traditional data access and retrieval functions;
3. DSS specifically focuses on features which make them easy to use by non-computer-proficient people in an interactive mode; and
4. DSS emphasizes flexibility and adaptability to accommodate changes in the environment and the decision making approach of the user.

Properly designed DSS is an interactive knowledge-based software system intended to help decision makers compile useful information from a combination of raw data, documents, and personal knowledge, or business models to identify and solve problems [8].

Typical information that a decision support application might gather and present includes:

– inventories of information assets (including legacy and relational data sources, data cubes, data warehouses, and data marts),
– comparative sales figures between one period and the next,
– projected revenue figures based on product sales assumptions.

The whole planning system is based on a hierarchical decision-making scheme. Nodes on it represent the decision centres. On those centres, the elementary estimations are carried out. These elementary decision-making procedures are carried out on the basis of different mathematical methods and systems. These elementary decisions could not be in conflict with each other. For this reason, there are coordination levels, which take care of the elementary decisions, analysing these and giving the rules for further activities. That means that modelling and optimization techniques are integrated with the expert system. The basic components of the system planning architecture are data storage, decision-making mechanism, knowledge base and interpreter. The last one has the following main activities: to call out the needed solution module, to analyse the obtained results, to generate the rules and instructions on the existence of contradictions, to issue the sorting and searching commands to the database. Through the interpreter, the revision of problem-solving is possible. A modular architecture guarantees the flexibility of the planning system. The result would be obtained on the basis of different modules and models. The order of using these modules must not be strictly determined. That kind of flexibility gives users more extensive goal.

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4. DECISION MAKING METHODS FOR INDUSTRIAL ROBOT-CELL COMPONENT SELECTION

Over the year many decision support systems (DDS) has been developed [9] to help decision makers to select most functional and cost-effective equipment for production cell. The complexity of the selection problem are related to economical, technical and social attributes, which are interconnected and may change in time. Economical attributes are likely to dependent on the market situation and entrepreneur’s investment certainty. Both parameters are hard to enquire and predict. Other hand technical parameters are readily available from machines data sheets and are easily compared. DDS should consider both qualitative and quantitative factors while selecting and evaluating correct solution. Some of the methods used in DDS are discussed below.

4.1. WEIGHTED SUM DECISION MODEL (WSM)

Weighted sum model is the simplest multi-criteria decision analysis method for evaluating alternatives by decision criteria. In this method [10], critical factors or performance values are assessed. In IR selection those critical values are derived from three categories: the minimal environmental conditions; the minimal performance conditions; and the budget ceiling. If proposed solution meets all the requirements (critical values) this can be considered as one alternative. The methods relays on expert’s opinions to value criteria weights, which can be summed at the decision matrices to rank alternatives.

4.2. DATA ENVELOPE ANALYSIS (DEA)

Data envelope analysis is a performance evaluation or benchmarking method where appreciable is assessed against the best practice. DEA model consist of inputs, decision-making units (DMU) and outputs. Inputs and outputs are performance measures and may or may not be directly linked to production process. DMU´s are units under evaluation which are composed performance metrics that characterize the units [11]. DEA evaluates minimum inputs against maximum output.

4.3. ANALYTIC HIERARCHY PROCESS (AHP)

Many of the decision support system are based on analytic hierarchy process (AHP), developed for use in complex decision making in 1980 by Saaty. The method and its refined successors [12, 13] are still widely used due to its ability to efficiently deal with objectives as well as subjective attributes. Methods first step is to build a problem hierarchy, containing criteria which importance are pairwise compared by different experts. Final step is obtaining and summarising composite performance scores for alternatives and making a final decision. The method has been improved by using Fuzzy numbers for linguistic expressions to pair-wise comparison of criteria [14].

4.4. TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO IDEAL SITUATION (TOPSIS)

TOPSIS is a method that compares a set of alternatives by expert group evaluated weights for criterion. Scores are normalised for each criterion and geometric distance between alternative ideal positive and ideal negative solution is calculated. The best solution is nearest to ideal positive solution and farthest from ideal negative solution. The method has been improved by using Fuzzy numbers for criteria analysis [15].

4.5. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial Neural Network method has been used in many applications where real world data variables are available [16]. ANN is a computing system that consist of nodes or artificial neurons, which are connected like synapses to transmit signal from input layer through one or many hidden layers to output layer. The main advantages of the method are so called learning effect from considering examples and ability to work whit great amount of data.

5. PROPOSED DUAL APPROACH MODEL

Most IR selection and decision making application includes only primary tasks – selecting the best type of industrial robot for a determined industrial task (welding, painting, assembly, machine tool servicing, and inspection, grinding and polishing or doing other manufacturing operations). Such a decision-making expert system has been developed and used for human resources development depending on needed skills and knowledge, whereas influence of human factor to productivity is larger when process is less automated [17]. Mapping of capabilities in managements systems described in [18] needs also input from process level.

However, at the same time, the robot cells are integrated into the manufacturing systems. This integration and different aspects of manufacturing were described in the ontology model (see Fig. 3). Proceeding from the manufacturing strategy and production principles of a company, new aspects will arise which are needed to take into consideration in the robot selection process (break-even point, increasing of productivity, OEE, etc.). All these are also directly connected to the products (product families) to be manufactured and to the task description (annual quantities, delivery times, batch sizes, quality and/or cost restrictions, etc.).

While the purpose of a primary or selection task is to check the robot's architecture and technical parameters best suited for a selected job, the reverse or prediction task consists of the analysis of optimal utilization of the implemented robot-cell in a company (see Fig. 4). Understanding the utilization of industrial robots in manufacturing will give us the main principles and decision-making rules for the optimal selection of industrial robots. Based on iterations of those tasks, we can derive optimal solution and estimate the accuracy of the decision.

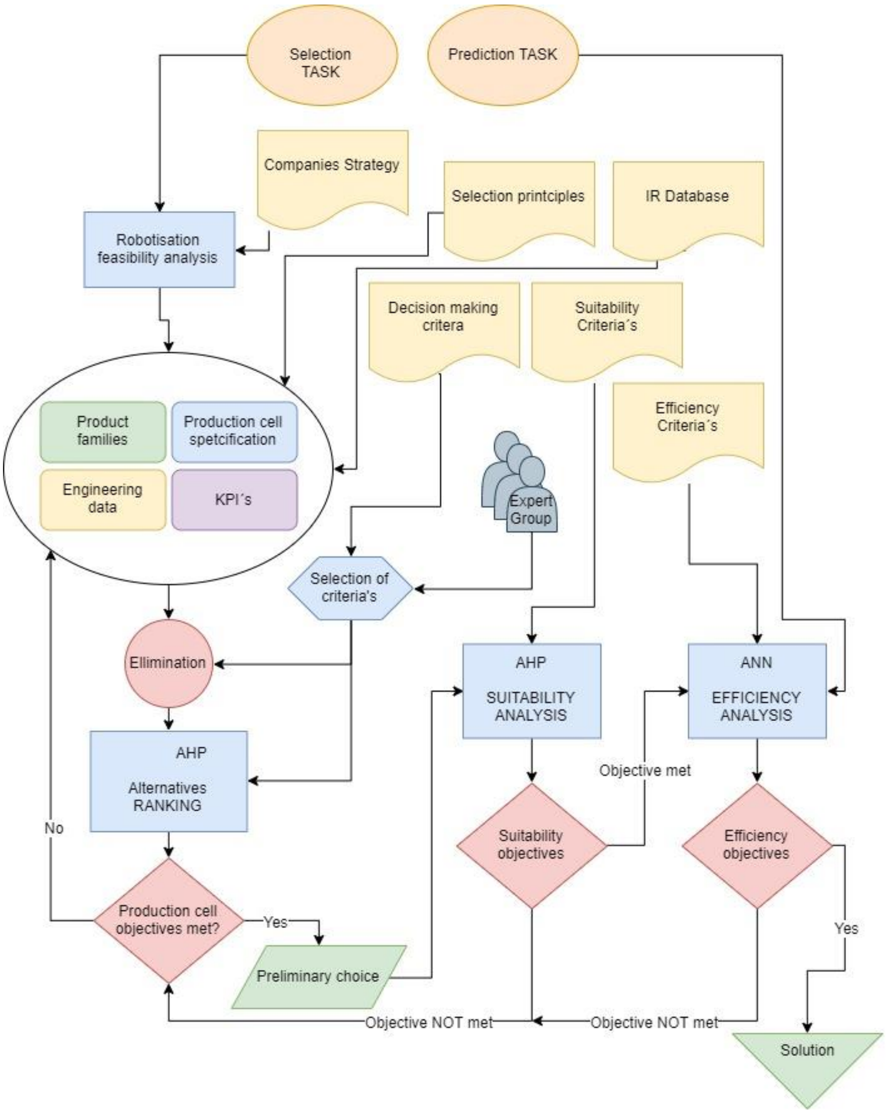

Fig. 4. Proposed DSS General Model

5.1. FEASIBILITY ANALYSIS AND ESTIMATION

Principle estimation on the bases of following criteria {Increase in productivity, lowering of production costs, improvement of the working environment, increasing the security of supply, quality assurance, workforce insurance, an increase of flexibility, stock depreciation}. The estimation could be calculated using different decision-making algorithms. We have used a self-adjustment algorithm (see one possible result on the Fig. 5).

5.2. THE SUITABILITY ANALYSIS

The suitability analysis is based on the task description. From the task description, the set of needed parameters {SNP} of an industrial robot (IR) would be determined. This set is formed based on the technological capabilities of an IR, which are crucial for fulfilling the industrial task. This set would be compared with the set of existing parameters of IR {SEP}. The largest common part will give the best result.

$$\text{Max} \quad \{SNP\} \cap \{SEP\}$$

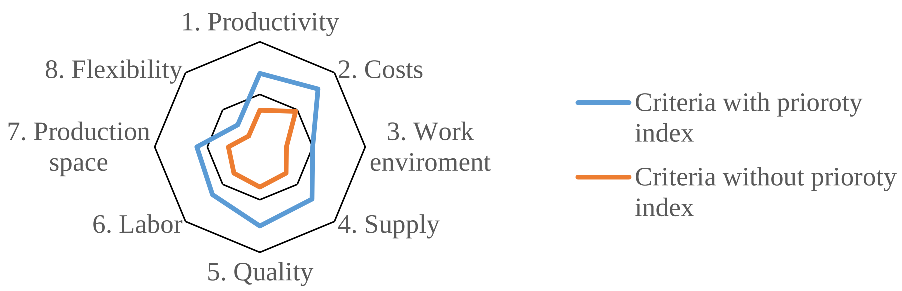

Fig. 5. Company feasibility analysis

We have used AHP based suitability analysis method [19], which uses product, technology and objective based parameters to evaluate suitability index. Expert group knowledge has been used for application-based criteria's evaluation. Future an ANN based prediction model together with fewer experts can be used for evaluating application-based criteria's [16]. For this study, IR welding application model has been used. Calculated indexes are compared to main suitability decision categories [19] for final assessment.

5.3. THE EFFICIENCY ANALYSIS

The efficiency analysis evaluates the designed or installed solution, based on best competences. For adequate estimation of production unit manufacturing efficiency and assessment of production unit process failures, the whole system, components and their relations must be evaluated [20, 21].

The output of a production unit are determined by the manufacturing task, which explains what is produced, which technologies are needed and which production type is used. The production type is one of the most important factors affecting productivity. According to production type (single, series or mass production), necessary technologies and equipment are selected. Those parameters and factors are summarised in Task Description. Selected technological capabilities and production program will form the production cell layout. In this case, selected system degree of flexibility is dependent on production equipment and their parameters for a chosen production program and layout. Depending on the flexibility of a production unit, it is possible to combine production structures to achieve minimum production time.

An outside factor affecting the efficiency of a production unit is the control over waiting times. The lack of balance in processing times and waiting times may result in production unit stalling or workplace congestion, which clogs the production flow and negatively affects Total Effective Equipment Performance (TEEP). Thus, one of the most important factors in assessing the efficiency of a production system is the degree of integration at a production unit. In the integrated system, it is possible to plan ahead and optimize the production flow to maximize Overall Equipment Effectiveness (OEE).

Prediction of manufacturing cell efficiency are performed by using Deep Learning (DL) ANN. An OEE prediction study comparing different machine learning algorithms have shown better reliability and performance dealing with given data [22].

DL is a neural network with a multilayer architecture capable of processing large amounts of data. While the architecture is significantly complex, DL algorithms are one of the best performing. Their performance will improve future by increasing the number of data. After every data iteration through ANN, back-propagation process is called and synapsis weights are adjusted using Gradient Descent, maximizing the correlation between the output and the residual error of the model [19]. The DL networks are built using Artificial Intelligence Techniques Inc., Neural Designer software. Technical parameters and operational data from similarly structured real production cell Manufacturing Execution Systems (MES) are used to train and test prediction model.

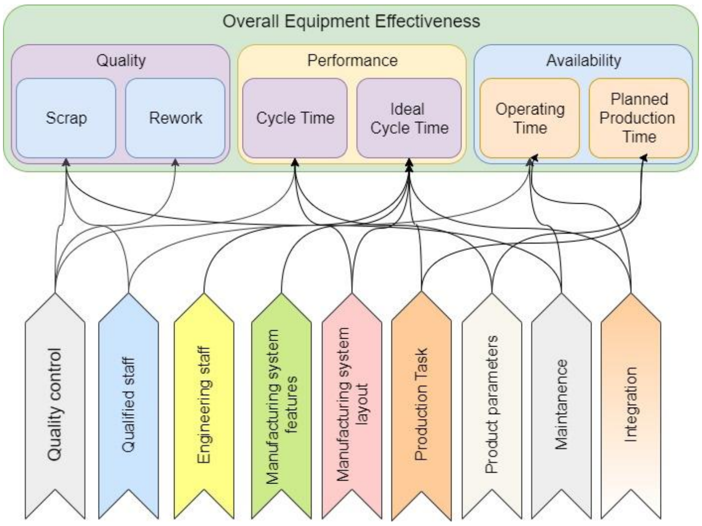

Fig. 6. OEE Prediction Model

The developed neural network are used to predicting production unite OEE [23] from input data shown on Fig. 6. After successful OEE prediction, company tactical and strategic KPI´s can be calculated. Theoretical break-even point (BEP), return on investment (ROI), payback period (PP) or discounted payback period (DPP) relations to the actual Gain of Investment (GI) were calculated among the other parameters.

6. CONCLUSION

Robotized production cells are complex systems and they consist of several specialty components. The selection of robots and all necessary components for robotized system design is not only a decisive task. Even less can be achieved by using available industrial robot classification systems. For a successful robot cell components selection, there are two prerequisites: firstly, we have to have a good overview of industrial robots and their technological capabilities; and, secondly, we have to assess the company's ability to integrate new systems to production and execution processes. To address those problem a concept model is proposed in which firstly a combined robot classification system together with robotisation feasibility analysis are performed. Subsequently, for achieving best possible results, a suitability and efficiency analysis loop are designed into the selection process. Suitability analysis is used to evaluate the selected solution correspondence to design requirements. As a last step an efficiency analysis is used to predict production cell parametrical model key performance indicators values. Both analysis steps are designed as a loop sub processes, in case of non-correspondence a previous step is again executed. Performing step iterations a optimal parametrical solution can be formed. Obtained results can be use to build and simulate virtual production cell model. Although each system component on its own has demonstrated good performance, the whole system still needs testing, and verifications. A proposed dual concept is an expedient approach because, on one hand, it is based on the analytic hierarchical task solving process of decomposition method; and on the other hand, systematically collected data allows us continuously to evaluate the system's operational efficiency in a company. On the basis of accumulated data, new knowledge is generated constantly, which can be used for robot selection, feasibility analysis and for the evaluation of results.

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