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# Development of Lean Hybrid Furniture Production Control System based on Glenday Sieve, Artificial Neural Networks and Simulation Modeling

## Razvoj sustava kontrole proizvodnje namještaja *Lean Hybrid* na temelju metode *Glenday sieve*, umjetnih neuronskih mreža i simulacijskog modeliranja

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**ABSTRACT •** *In the paper, by way of background, the role of Polish furniture industry in the world and in Europe is discussed and current trends in the field of furniture manufacturing management are presented. Further, an analysis of the technological process in a furniture company is performed and the research questions are identified. Based on this, the main aim of the research is provided – a concept of a new lean production control system based on Glenday sieve, artificial neural networks and simulation modeling. The aim of the present approach is to plan and execute the production program effectively and maximize the use of workstations at variable and hardly predictable demand for sets of furniture. The paper presents the methodological approach, results and discussion on the suggested solution.*

**Key words:** *production planning system, Glenday sieve, artificial neural networks, simulation modeling, furniture industry, industry 4.0*

**SAŽETAK •** *U radu je predstavljena uloga poljske industrije namještaja u svijetu i Europi te trendovi u području upravljanja proizvodnjom namještaja. Nadalje, provedena je analiza tehnološkog procesa u poduzeću za proizvodnju namještaja i identificirane teme istraživanja. Na temelju toga definiran je osnovni cilj istraživanja – koncept novog sustava lean kontrole proizvodnje koji se temelji na metodi Glenday sieve, umjetnim neuronskim mrežama i simulacijskome modeliranju. Cilj opisanog pristupa jest učinkovito planiranje i izvršavanje proizvodnog programa te maksimalna iskorištenost proizvodnih kapaciteta pri promjenjivoj i teško predvidivoj potražnji namještaja. Rad prikazuje metodološki pristup, rezultate i raspravu o predloženom rješenju.*

**Ključne riječi:** *sustav planiranja proizvodnje, metoda Glenday sieve, umjetne neuronske mreže, simulacijsko modeliranje, industrija namještaja, industrija 4.0*

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## 1 INTRODUCTION
## 1. UVOD

In the contemporary global market, furniture manufacturers are facing strong competition (Zadnik Stirn *et al*. 2016). In order to maintain their market share, they have to improve their manufacturing and management processes and introduce innovations both in products and processes, as well as to be familiar with the consumer's needs (Fabisiak 2017, Oblak *et al*. 2017).

The main objective of every furniture company is an efficient business (Hrovatin *et al*. 2015). To achieve this goal, companies are forced not only to produce their furniture using high-quality and precise machinery and equipment but also to manage and control their process in an effective way. To do that properly in the floating environment and bearing in mind lumpy and intermittent customer's demand, companies have to plan their production in a very efficient, yet agile and flexible manner. Effective demand forecasting is essential for the companies, where ensuring the continuous and fault-free operation is required (Rosienkiewicz *et al*., 2017). The well-calculated demand forecasting is crucial to reduce purchase volumes and to optimize stocks (Santin *et al*., 2015). In his paper, Kolassa (2016) discusses about the big data trend in terms of retail sales forecasting. According to his research, operational forecasting in retail should be conducted not only at highly aggregated levels, but possibly at a most fine-grained level, i.e. for count data and intermittent demands.

According to the EU report on the furniture market (Centre for European Policy Studies, 2014), Poland is one of 10 top countries of world furniture production (2 % of world production). Although economic recession has strongly influenced the operation of the companies focused on wood processing and furniture manufacturing during the last several years (Jelačić *et al*., 2012), it can be noticed that furniture production in the EU is slowly recovering from the period of weakness. Italy, Germany, and Poland – Europe's three largest furniture producing countries – "all raised their output in 2014 and early 2015. Furniture production in Poland increased particularly sharply last year and in the first quarter of 2015" (ITTO, 2015). This situation encourages Polish furniture producers to invest in their factories, to enlarge them and to implement innovative solutions enhancing management processes, especially now – in the era of Industry 4.0. The term "Industry 4.0" comes from the name of the project, started by the German government for their high-tech-strategy, which has been developed to take advantage of recently emerged disruptive technologies including i.a.: Cyber-Physical Systems, Artificial Intelligence, Internet of Things and Services (IoTS), Big data, Augmented Reality. It is considered as the beginning of the fourth industrial revolution, which mainly refers to the digitization of industry. It is expected that it will fundamentally change the production methods and business models presently used in industrialized countries. Recently, certain producers, who have started implementing technology of IoTS, focused their sales on the Internet channel. The online sales market in the furniture industry is not very developed in Poland. Even IKEA started selling furniture via Internet only in February 2017 and this service is still in a pilot phase. However, this sales channel will be developing in the years to come. It is expected that IoTS, one of the pillars of Industry 4.0, will play a major role in the furniture industry in the near future.

As Perić *et al*. noticed, it is important to underline that wood industry is a resource-intensive industry, and as such does not have a high added value, yet is important to the national economy (Perić *et al*., 2017). Therefore, in cases of furniture companies, especially the SMEs, it is crucial to invest in knowledge, knowledge management and technology in order to be competitive on the market. It is a rather well-known trend that a lot of solutions, methods and tools are first developed in the automotive industry and other high-tech branches, and then they are implemented into less-automated sectors, like the mining or wood industry (Chlebus *et al*., 2015).

The Authors performed a literature review to analyze which aspects of production management in the furniture industry have been recently researched. Previous research studies of production management in the furniture industry indicate that Computer Aided Design (CAD) software is nowadays conventionally used in furniture companies (Hrovatin *et al*., 2015). Usage of the MRP or ERP systems is almost a standard, yet for companies that want to be more agile and flexible, this is not enough. These companies have to implement more advanced solutions (based e.g. on artificial intelligence). Santin *et al*. (2015) suggest an approach of minimizing the difference between production and demand based on ABC analysis and forecasting sales volumes on a quarterly basis implemented in the MRP system. According to Perić *et al*. (2017), the ERP systems are mainly used for the financial module, human resources, management, and production processes, purchasing and sales management. The issue of the supply chain management was discussed by many researchers. Zhang and Zhang (2007) investigated the implementation of the simulation approach to quantify the benefit of the demand information sharing in a three-tier supply chain model, whereas Robb *et al*. (2008) developed a model exploring relationships between supply chain/operations practice and operational/financial performance in a Chinese furniture manufacturer. In their research, Caridi *et al*. (2012) discussed whether supply chain choices depend on product modularity and innovativeness, and how supply chain choices can be aligned to these product features to maximize performance. Optimization of furniture production was analyzed in a technological aspect by Oliveira *et al*. (2016) and in a managerial aspect by Alem and Morabito (2012). Oliveira *et al*. (2016) presented an information system for the furniture industry to optimize the cutting process and the generated waste, while other mentioned authors were focused on the application of a robust optimization to production planning in furniture manufacture under data uncertainty.

Further, the literature review shows a promising research carried-out by Yao and Carlson (2003) on an agile furniture production concept based on MRP, JIT and TQM. In the paper of Massote and Santi (2013), an implementation of a cleaner production program in a Brazilian wooden furniture factory is described, showing that the trends for eco-friendly production can be observed not only in automotive industry. Rosa and Beloborodko (2015) suggested a decision support for the development of industrial synergies based on case studies of Latvian brewery and wood-processing industries. Guimarães *et al*. (2016) presented the results of their research on Brazilian furniture industry considering product innovation and organizational performance. These papers prove that a lot has been done to enhance and support furniture production from the research point of view.

Literature review presented by the Authors shows that there are many solutions implemented from automotive sector to wood or furniture industry, yet there is a lack of a comprehensive approach that would begin with an analysis of the demand and finish on production planning and control. In any manufacturing company, importance of furniture production management and control can not be overemphasized. An efficient control system based on accurate production plan influences agile production and realization of production orders. Therefore, the main aim of the paper is to develop a concept of a dedicated lean production control system, which would make it possible for a company to plan and execute its production program effectively, maximizing the use of workstations at variable and hardly predictable demand for furniture sets. The proposed solution is based on lean management, Artificial Neural Networks (ANNs), and simulation modeling. ANNs, being mathematical models for representing the biological processes of the human brain (Segall, 1995), for some time now have been advocated as an alternative to traditional statistical forecasting methods.

### 1.1 Development of a new production control system
### 1.1. Razvoj novog sustava kontrole proizvodnje

This paper is a summary of the research carried out for a company (described in section 2.5) from the furniture industry. In the company, whose key marketing channel is the online marketing channel, it was decided to develop a new production system that would result in increased effectiveness and production volume, delivery time reduced to 48 hours (in the online sales channel) and more precise sales forecasts, which, in turn, would result in improved production planning. All those features require implementation of Industry 4.0 technologies. Development of such a manufacturing system is a complex and multi-stage process. During the works on developing a dedicated system, several research questions appeared:

- In what way the sales level can be forecasted, when the company has no sufficient available base of reliably acquired statistic data?
- In these circumstances, how a set of explanatory variables should be constructed?
- In what way, at diversified demand (series production and individual, customized orders), the manufacturing process should be controlled?
- In what way the production strategy for various product types should be elaborated?
- How to verify whether the designed system will be immune to disturbances?

### 1.2 Demand forecasting problem
### 1.2. Problem predviđanja potražnje

Demand forecasting is an issue of large uncertainty and characterized by fluctuations. In order to solve this problem in the abovementioned company, future demand values were exactly analyzed, so that real demand could be characterized. According to the approach proposed by the Authors, the examination began from demand analysis and trial forecasts in daily terms. Preliminary results showed that the furniture demand is of a lumpy, intermittent nature and often takes the zero value. Demand forecasts in daily terms, both obtained by traditional methods and based on Artificial Neural Networks (ANNs) executing regressive relationships, were burdened with very high errors (see Appendix). For this reason, it was decided to perform the calculations in aggregated, monthly terms, which is a common practice in data science. The next problem hindering determination of effective forecasts was that the data required to build the ANNs executing regressive relationships, based on explanatory variables, were unavailable in the company. For this reason, the Authors decided to apply a hybrid approach in which the forecasts obtained by traditional methods (moving average (MA), exponential smoothing (SES) and naïve method) would play the role of some explanatory variables.

### 1.3 Pull system
### 1.3. Sustav povlačenja

Mass production of furniture with use of pressboards in the conditions of strong competition enforces low price and short delivery time. Large numbers of coloristic variants of the offered furniture, combined with large numbers of dimensions of individual cabinets, make storage of finished products impossible. Therefore, satisfying the customers' demand by collecting goods from the stock of finished products is impossible, even if these products are stored in packages to be individually assembled by the customers themselves. At the above-mentioned boundary conditions, the best solution would be basing the production system on the Lean Manufacturing concept and, in particular, on the sequential pull system and the replenishment pull system as suggested by Smalley (2009).

In the replenishment pull system, stocks of finished products from each group (after segmentation of products) are maintained, and manufacture is initiated only after shipment of individual products from the warehouse to the customer (necessity to replenish the stock). In this system, finished products can be shipped immediately after receiving the order. In the sequential pull system, manufacture is initiated upon a specific customer's order, at the moment of its receipt only. The production order is directed to the first manufacturing operation. However, this type of pull system is difficult to be implemented in the case of long takt time, unstable production processes and small availability of machines (Fulczyk, 2017).

Determination of inventory in the replenishment pull system will be based on the results of forecasts coming from the ANNs. In turn, all errors of the forecasts will be currently corrected by starting the sequential pull system.

### 1.4 Glenday sieve
1.4. Metoda *Glenday sieve*

Another problem to be solved is determining which product should be qualified to manufacture in the sequential pull system, and which to manufacture in the replenishment pull system. In this case, the Authors decided to use the Glenday Sieve. The Glenday sieve is a "method for identifying high-volume production processes upon which to focus process improvement initiatives. The Glenday sieve approach states that a small percentage of procedures, processes, units or activities account for a large portion of sales, and includes a color-coding system for labeling processes by output volume" (WebFinance, 2017). The Glenday sieve classifies products in four categories (Kerber, 2007): green – high volume items that are probably already produced frequently, yellow – encounter real barriers against introducing manufacture of each product in each cycle; blue –include materials and procedures introducing the additional complexity, adding no value for the customer; red – a question should be asked about rationality of manufacture and sales of these products. It was assumed that another production line should be built and added to the sequential pull system for unpredictable, individual and customized orders.

### 1.5 Simulation modeling
1.5. Simulacijsko modeliranje

As Zhang and Zhang (2007) state, implementation of a simulation enables the decision makers to examine changes in a part of the chain and subsequent consequences with less expense than would be required for a field experiment, which is usually difficult to be carried out. Therefore, in the present approach, the simulation was implemented. Within the solution of the issue that is connected with the possibility to verify whether the designed system will be resistant to disturbances, it was decided to build a simulation model of the manufacturing system of kitchen and bathroom furniture for the observed company. In this model, among others, it is possible to verify loads of machines and workers, to optimize the workshop layout, to introduce random failures and disturbances, as well as to evaluate a response of the designed control system to these occurrences.

### 1.6 Analysis of technological process
1.6. Analiza tehnološkog procesa

The analyzed company deals with the production of kitchen and bathroom furniture. It is located in the Wielkopolska region, the center of Polish cabinet furniture industry. The company has a wide range of models and patterns of manufactured products. This results in a large number of furniture variants to be made for a customer's order. The number of furniture variants $V_{\text{furniture}}$ is obtained by multiplying numbers of variants of bodies $V_B$, fronts $V_F$, handles $V_{Ha}$, hinges $V_{Hi}$ and muntins $V_M$:

$$V_{\text{furniture}} = V_B \cdot V_F \cdot V_{Ha} \cdot V_{Hi} \cdot V_M. \tag{1}$$

Even with limited variant numbers of bodies and fronts or handles, hinges and muntins, the number of furniture variants – determined by the formula (1) – soon exceeds 20 000 pieces. There is no physical possibility to maintain stocks of furniture in this size; it is hard to imagine dimensions of such a warehouse and its maintenance costs. The storage space is also often restricted by the area of industrial plot at the company disposal. In addition, the number of variants should be enlarged by in-stock level for each variant.

It can be observed that, to preserve low manufacturing costs, furniture cannot be manufactured for stock because of too large number of variants. On the other hand, customers cannot accept a long time of waiting for the ordered furniture; waiting times in the furniture industry often reach 5 or 6 weeks. So, the furniture delivery time is an important competitiveness factor and customers often decide to buy from the manufacturer who delivers the products faster.

In the analyzed company, manufacturing of cabinet furniture proceeds according to the schedule of production and set order of technological operations. A diagram of the manufacturing process, written in the IDEF0 notation is shown in Fig. 1, where individual technological operations are represented in consecutively numbered A1- A6 boxes.

To satisfy the opposing requirements (unpredictable demand, production time longer than the order execution time, etc.), the company manufactures and stores bodies and face panels of the cabinets separately. Most often, the bodies appear in several colors and sizes, and face panels. In the warehouse, after receiving an order for a specific furniture set, bodies are combined with proper face panels in selling sets. At this stage, the order is completed with handles to the doors and drawers, hinges and other shopping items.

## 2 METHODS
2. METODE

The methodology of building a complex, lean hybrid production system that would increase production effectiveness and volume, as well as provide more precise production planning based on the Glenday sieve, ANNs and simulation modeling, is composed of several stages, as shown in Fig. 2.

The first stage is an analysis of a vast range of products using the Glenday Sieve (Glenday 2007). The manufactured wooden furniture was subjected to detailed analysis on the basis of historical data concerning production volume and frequency of customers orders. Based on that, four groups of products were created and three paths were selected: green stream (50

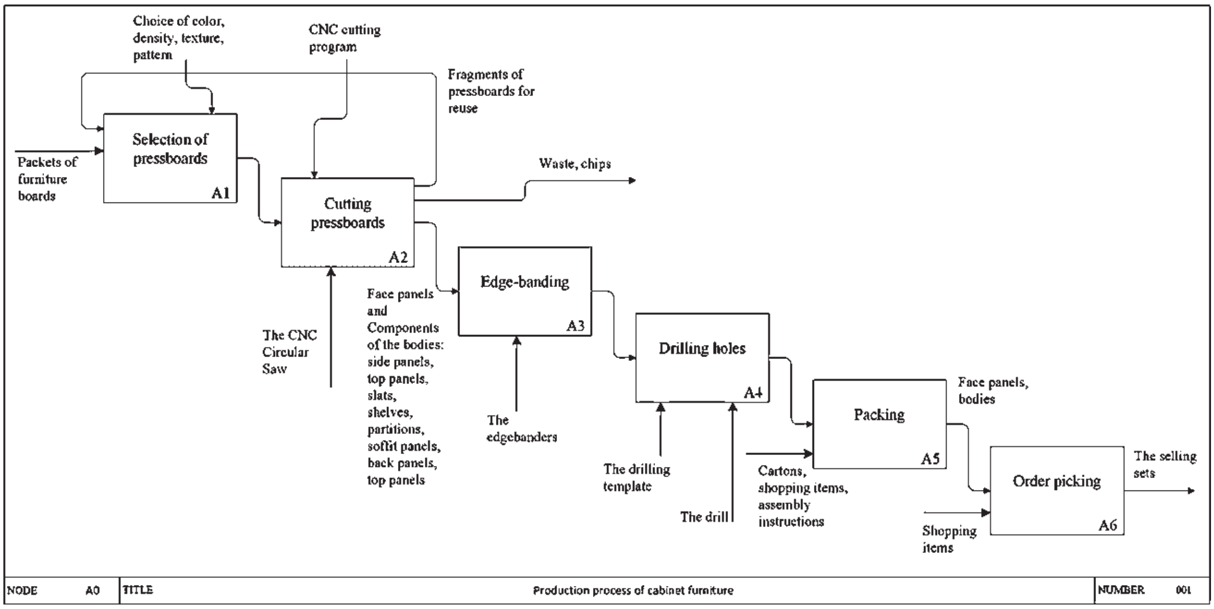


**Figure 1** Diagram of cabinet furniture manufacturing process, created in IDEF0[1]
**Slika 1.** Dijagram procesa proizvodnje korpusnog namještaja, izrađeno u IDEF0

% of sales volume – mass production) – production forecast based on the ANN approach; blue and yellow streams (respectively up to 40 % and 10 % of sales volume – single order production) – production based on compensation of forecast errors; red stream (less than 1 % of sales volume) – shutdown of production.

On the basis of the forecast results, the required number of machines $i_0$ is calculated based on $i_0$ rate:

$$i_0 = \frac{\sum_{i=1}^{n} \left( setup\,time + n \cdot run\,time \right)}{\Psi_d \cdot D \cdot I \cdot h}, \qquad (2)$$

Where is $n$ – No. of pieces, $\Psi_d$ – factor of day utilization, $D$ – No. of days, $I$ – No. of shifts, and $h$ – No. of hours/shift.

According to the determined number of necessary machines, the simulation model should be built.

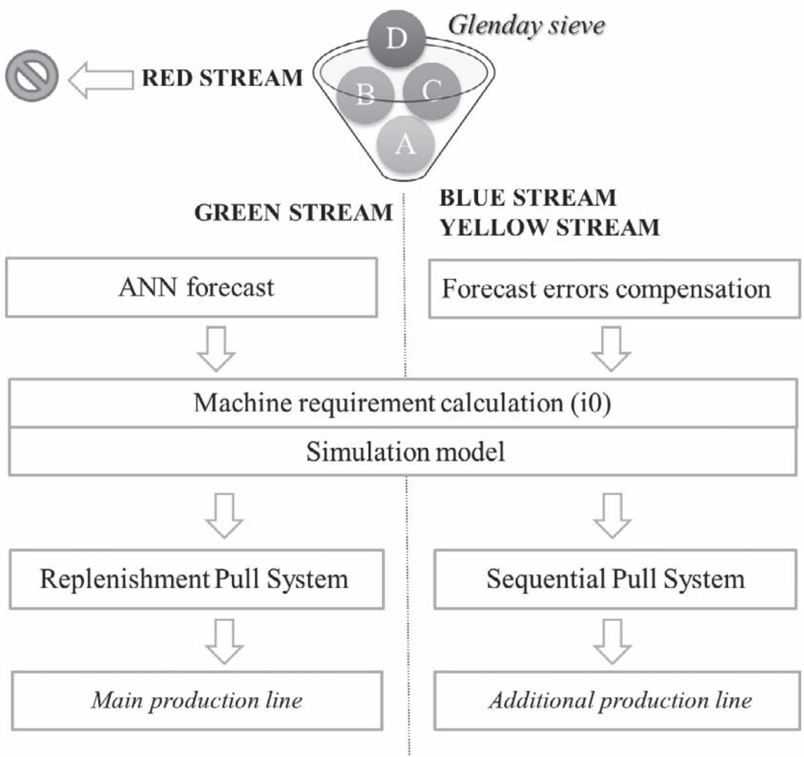


**Figure 2** The concept of Lean Hybrid Furniture Production Control System
**Slika 2.** Koncept sustava kontrole proizvodnje namještaja *Lean Hybrid*

[1] *IDEF refers to a family of modeling language, where IDEF0 is Integration DEFinition for Function Modeling.*

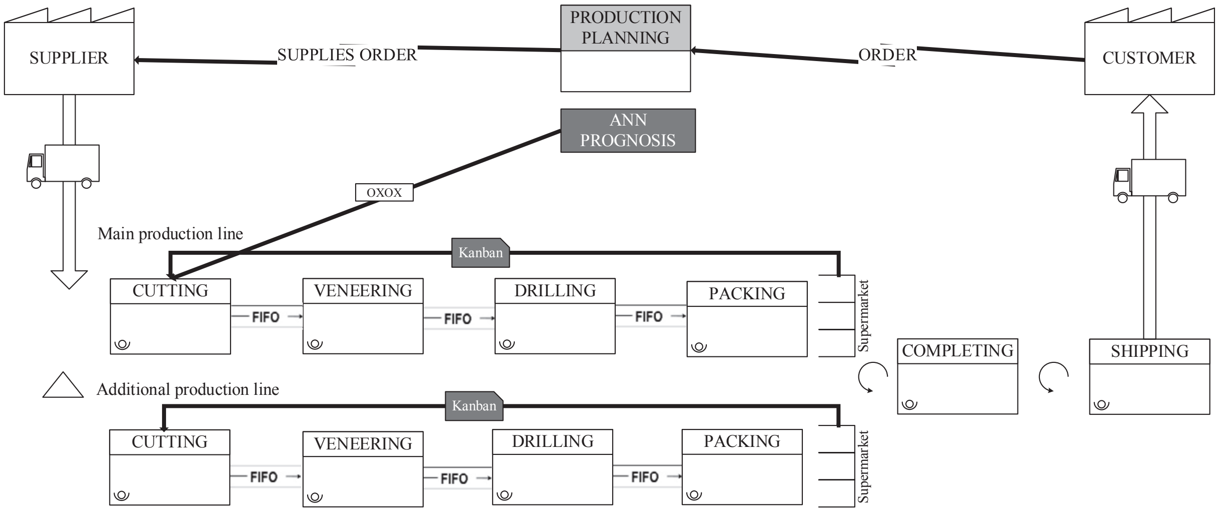


**Figure 3** Current State Value Stream Map
**Slika 3.** Trenutačno stanje karte toka vrijednosti

Based on results of the simulation model (loads of machines and workers, optimization of the workshop layout, introduction of random failures and disturbances, as well as evaluation of a response of the designed control system to these occurrences), two paths should be used for the production systems:

1. for green products stream – Replenishment Pull System used in the main production line;
2. for blue and yellow products stream – Sequential Pull System used in the additional production line.

The main production line will use highly efficient machines for wood cutting, veneering, drilling and packing, while the additional production line will consist of smaller and less expensive machines. Both lines should have a Supermarket after the packing workstation, where all the elements, ready for completing, will be stored. When the products are completed from the supermarket, a production Kanban card will be moved to the first workstation in the line, giving a signal to start production of the taken element. The Current State Value Stream Map (Fig. 3) of wooden furniture production and Future State Map (Fig. 4) with the suggested changes are presented below.

According to the above-presented concept of production control system, forecasts for the green parts to be considered during production planning by means of a simulation model will be determined on the ground of the ANN. A diagram of building an ANN is shown in Fig. 5 below (MA stands for moving average, k is number of periods, SES stands for single exponential smoothing, α is a smoothing constant, x is an explanatory variable).

As mentioned above, because of unsatisfactory calculated forecasts of daily demand for selected types of furniture (caused by a shortage of available historical data), the analysis was carried-out in aggregated, monthly terms. From statistical point of view, a disadvantage of this approach (aggregation) is a significant reduction of the sample size (at daily forecasting it should be at least several hundred (n>400) and at monthly forecasting – because of missing data from previous periods – it should range between 17 and 23 observations). Usually, the more observations, the more precise are the forecasts, because the prediction models can better identify periodicity, seasonal relationships, and data trends. For the research and development purpose, a simulation model of the analyzed production system was developed, taking into account the following components of the system: workstations, components and parts of the products, transportation paths, production resources – workers and means of transport, manufacturing processes, and production plans.

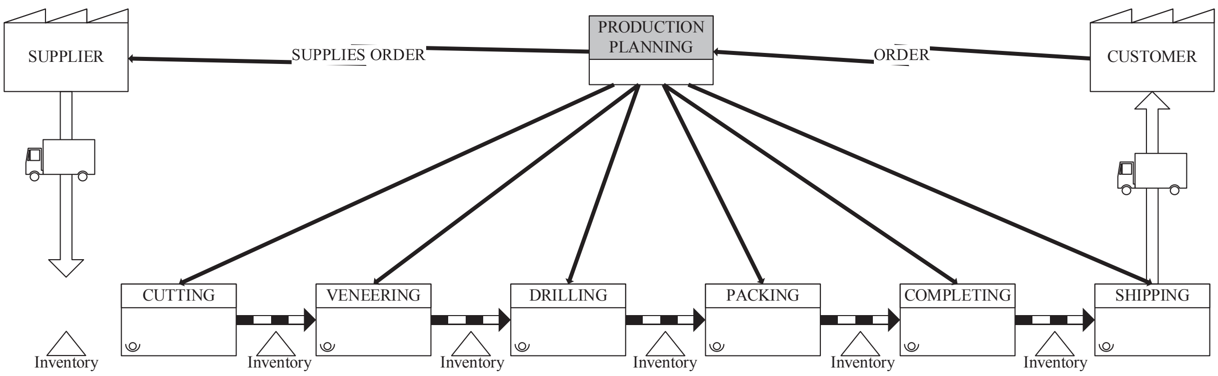


**Figure 4** Future State Value Stream Map
**Slika 4.** Buduće stanje karte toka vrijednosti

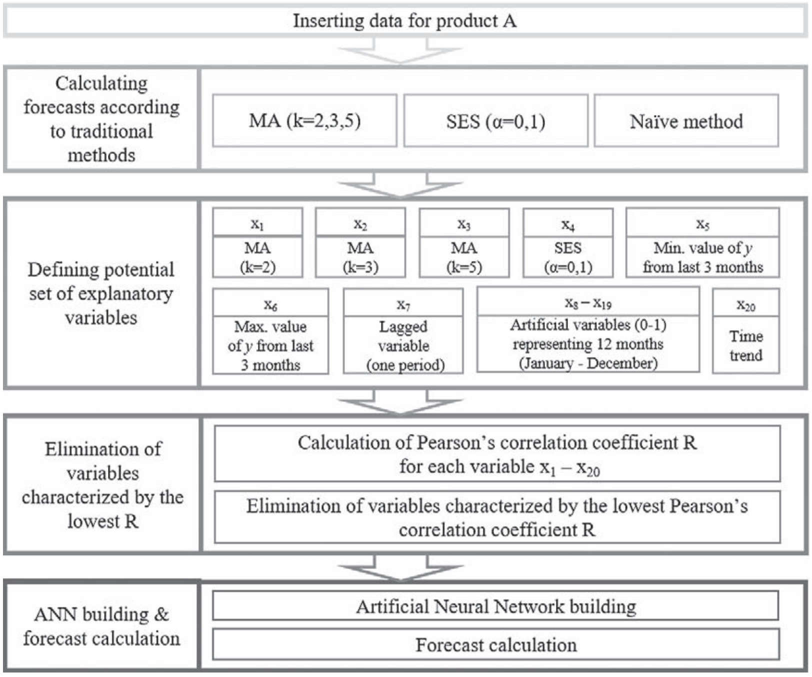


**Figure 5** Hybrid algorithm for forecast calculation
**Slika 5.** Hibridni algoritam za proračun predviđenih vrijednosti

Next, the simulation model was subjected to numerous simulation examinations in order to validate it, comparing the effectiveness of the model – at specifically limited production resources – with its existing equivalent.

## 3 RESULTS AND DISCUSSION
## 3. REZULTATI I RASPRAVA

In the analyzed company, 76 types of cabinet furniture are manufactured (without color differentiation). After analysis of the product line by the use of the Glenday Sieve, the products were assigned to the following groups: green stream – 15 products, yellow stream – 23 products, blue stream – 16 products, red stream – 22 products. On this ground, the furniture types were selected: the types that should be removed from the offer (red stream) and the types that should be applied for the two kinds of manufacturing approach. For the green-stream products – manufacture should be started in the main production line on the basis of the ANN forecasts, for the yellow- and blue-stream products – manufacture should be started in the additional production line based on real customer's demand. For further analysis, the green-stream products are designated by the characters from A to O so as not to disclose the company's data.

For each analyzed type of furniture (A-O), an ANN network was constructed in the Statistica 12.0 program. Characteristics of individual networks: sample size, variables being inputs to the ANN ($x_1$-$x_{20}$), the network structure: multilayer perceptron (MLP) and supervised learning algorithm (Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm), quality of learning, testing and validation are presented in Table 1 below. The table also shows the determined relative forecast errors ex-post for each type of furniture. To compare the effectiveness of the forecasts coming from the ANN, the forecasts were also calculated by traditional methods: moving average (MA) for k = 2, 3 and 5, exponential smoothing (SES) and naïve method.

The obtained effectiveness values for all the examined furniture types indicate that the most effective method of monthly sales forecasting for 13 out of 15 types are artificial neural networks. The ANNs appeared less effective in sales forecasts of the products A and B only (error >= 40 %). However, it should be emphasized that sample size in these cases was n=17 observations only, so the results are hardly reliable. The analysis of effectiveness levels of the forecasts also shows that values of the relative forecast error ex-post did not exceed 40 % for over 85 % of the furniture types. This result is much better than that obtained for the daily sales forecasting. The ANN forecast error values ranged between 15 % (min.) and 55 % (max.), with the average value for 15 furniture types equal to 31 % (median 27 %). Even if significant, these errors can be found acceptable, considering the modest number of observations.

On the grounds of the forecasts calculated with use of ANNs, a production schedule was prepared and then numbers of machines required for the execution of the assumed plan were calculated according to the formula (2). The results are given in Table 2.

This way a determined number of production machines was verified by the simulation model. This is an important part of the present method since the expression for $i_0$ does not consider i.a. the time of waiting for the machine operator (resulting from his moving between machines) or the time for transporting the elements between machines. The simulation model also makes it possible to observe the dynamics of load changes of the analyzed workstation, see Fig. 6.

**Table 1** ANN characteristics and Relative Forecast Error ex-post for each analyzed method
**Tablica 1**. ANN karakteristike i relativna pogreška predviđanja *ex-post* za svaku analiziranu metodu

| Product / *Proizvod* | | Sample size (n) *Veličina uzorka* | ANN characteristics / *ANN karakteristike* | | | | | | Relative Forecast Error ex-post *Relativna pogreška predviđanja* ex-post | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Variables *Varijable* | ANN structure *Struktura ANN-a* | Quality (training) | Quality (testing) | Quality (validation) | Learning algorithm *Algoritam učenja* | ANN | MA (2) | MA (3) | MA (5) | SES | Naïve method |
| 1 | A | 17 | *x*1-*x*3; *x*5-*x*7; *x*17; *x*19 | MLP 8-5-1 | 0.999 | 0.397 | 0.72 | BFGS 17 | 40 % | 36 % | 41 % | 48 % | **33 %** | **33 %** |
| 2 | B | 17 | *x*1; *x*5; *x*7; *x*11; *x*20 | MLP 5-3-1 | 0.818 | 0.885 | 0.129 | BFGS 5 | 52 % | **44 %** | 46 % | 48 % | 47 % | 47 % |
| 3 | C | 20 | *x*1-*x*4; *x*6; *x*7; *x*10; *x*20 | MLP 8-11-1 | 0.781 | 0.663 | 0.862 | BFGS 21 | **37 %** | 56 % | 51 % | 54 % | 65 % | 65 % |
| 4 | D | 20 | *x*1-*x*7; *x*16; *x*20 | MLP 9-5-1 | 0.814 | 0.808 | 0.999 | BFGS 6 | **36 %** | 50 % | 56 % | 59 % | 48 % | 48 % |
| 5 | E | 20 | *x*2-*x*7; *x*19; *x*20 | MLP 8-12-1 | 0.638 | 0.951 | 0.994 | BFGS 3 | **55 %** | 83 % | 69 % | 67 % | 81 % | 81 % |
| 6 | F | 20 | *x*1-*x*7; *x*10; *x*20 | MLP 9-10-1 | 0.98 | 0.905 | 1 | BFGS 51 | **20 %** | 48 % | 46 % | 48 % | 51 % | 51 % |
| 7 | G | 23 | *x*1-*x*20 | MLP 20-9-1 | 0.996 | -0.55 | 0.838 | BFGS 0 | **24 %** | 32 % | 34 % | 38 % | 36 % | 36 % |
| 8 | H | 23 | *x*1-*x*20 | MLP 20-8-1 | 0.762 | 0.862 | 0.995 | BFGS 3 | **27 %** | 42 % | 43 % | 47 % | 51 % | 51 % |
| 9 | I | 23 | *x*1-*x*20 | MLP 20-15-1 | 0.942 | 1 | 1 | BFGS 6 | **23 %** | 30 % | 38 % | 50 % | 36 % | 36 % |
| 10 | J | 23 | *x*1-*x*20 | MLP 20-14-1 | 0.99 | 0.471 | 0.744 | BFGS 0 | **39 %** | 45 % | 42 % | 47 % | 47 % | 47 % |
| 11 | K | 23 | *x*1-*x*20 | MLP 20-13-1 | 0.676 | 0.962 | 0.522 | BFGS 3 | **34 %** | 42 % | 38 % | 40 % | 42 % | 42 % |
| 12 | L | 23 | *x*1-*x*7; *x*20 | MLP 8-6-1 | 0.949 | 0.823 | 1 | BFGS 28 | **23 %** | 46 % | 42 % | 49 % | 51 % | 51 % |
| 13 | M | 20 | *x*1-*x*7; *x*11; *x*19; *x*20 | MLP 10-6-1 | 0.912 | 0.973 | 0.658 | BFGS 34 | **22 %** | 74 % | 71 % | 65 % | 84 % | 84 % |
| 14 | N | 23 | *x*1-*x*20 | MLP 20-8-1 | 0.985 | 0.945 | 0.958 | BFGS 17 | **22 %** | 52 % | 54 % | 53 % | 61 % | 61 % |
| 15 | O | 21 | *x*1-*x*7; *x*13; *x*20 | MLP 9-4-1 | 0.968 | 0.445 | 0.9 | BFGS 37 | **15 %** | 50 % | 45 % | 45 % | 60 % | 60 % |

**Table 2** Required number of machines $i_0$ calculation
**Tablica 2.** Broj strojeva potreban za izračun $i_0$

| **Machine type** / *Vrsta stroja* | $i_0$ | **Number of machines** *Broj strojeva* |
|---|---|---|
| Saw / *stroj za piljenje* | 3.29 | 4 |
| one-sided edge banding machine / *stroj za jednostrano oblaganje rubova* | 2.47 | 3 |
| four-sided edge banding machine / *stroj za četverostrano oblaganje rubova* | 0.46 | 1 |
| drilling machine / *bušilica* | 2.09 | 3 |
| drilling machine for small elements / *bušilica za male elemente* | 0.59 | 1 |
| packing station / *stroj za pakiranje* | 1.33 | 2 |

Loads of the machines result from their covering with technological operations (and numbers of the manufactured parts) and retooling when the manufactured product is to be changed. Comparison of verified loads of the machines and facilities is shown in Fig. 7.

Apart from percentage loads of the machines, Fig. 7 shows waiting time for a resource (e.g. for the operator; the machine can not start working without his execution of some initiating actions). Another element, not included in loads of the machines and facilities, according to the formula for $i_0$, is waiting time for removing the machine in the case when there is no place to put it aside (the buffer behind the machine is 100 % filled and the parts are not conveyed to another workstation because they are waiting for a transport means or for a free place in the buffer). In this condition, the machine is counted as blocked.

In the analyzed case, a verified load of the machines never exceeds 100 %, so it can be acknowledged that the forecast production plan is realizable and the customer's order should be executed within 48 hours.

## 4 CONCLUSIONS
## 4. ZAKLJUČAK

The main aim of the present research was to develop a dedicated lean production control system for a furniture company operating in the Internet environment, which would enable the production program to be planned and executed effectively, with maximum use of wood-processing workstations at variable and hardly predictable demand for furniture. Implementation of such a system makes it possible to obtain significant benefits, fitting the needs of Industry 4.0. According to the presented methodology, application of the Glenday sieve permits the wooden products to be classified into two groups. One group of products will be manufactured according to the forecasts obtained by

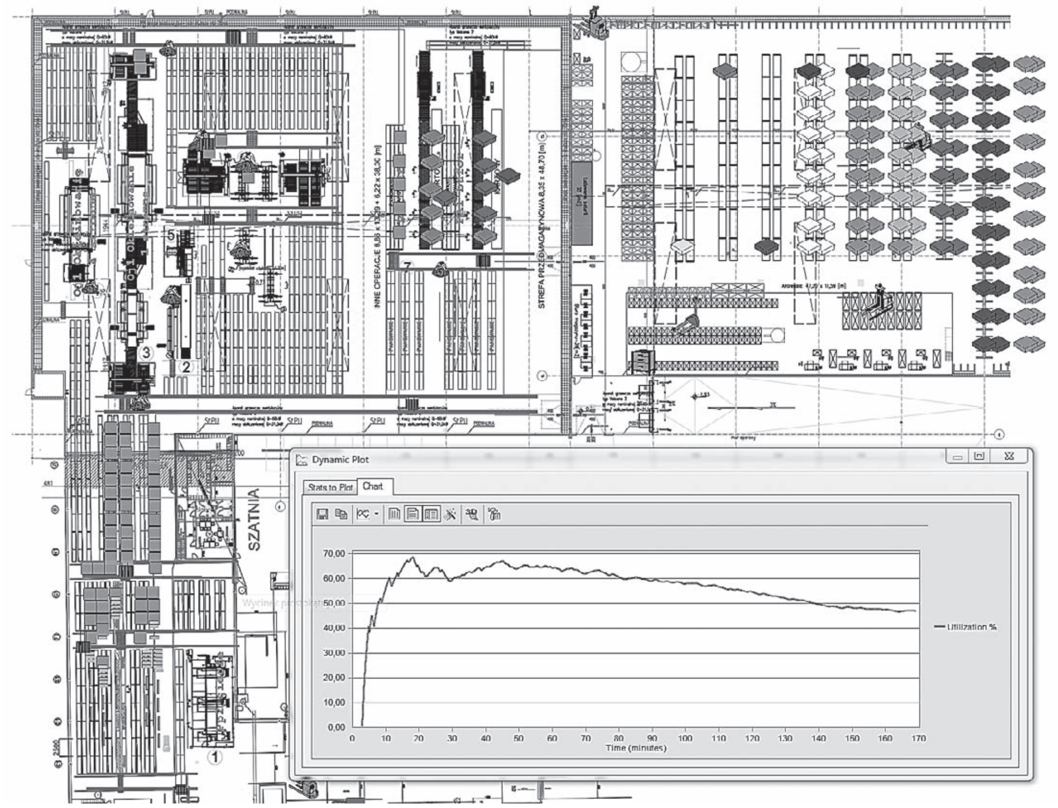


**Figure 6** Load changes of the analyzed workstation during simulation examinations
**Slika 6.** Promjene opterećenja analiziranih radnih postaja tijekom simulacijskih pregleda

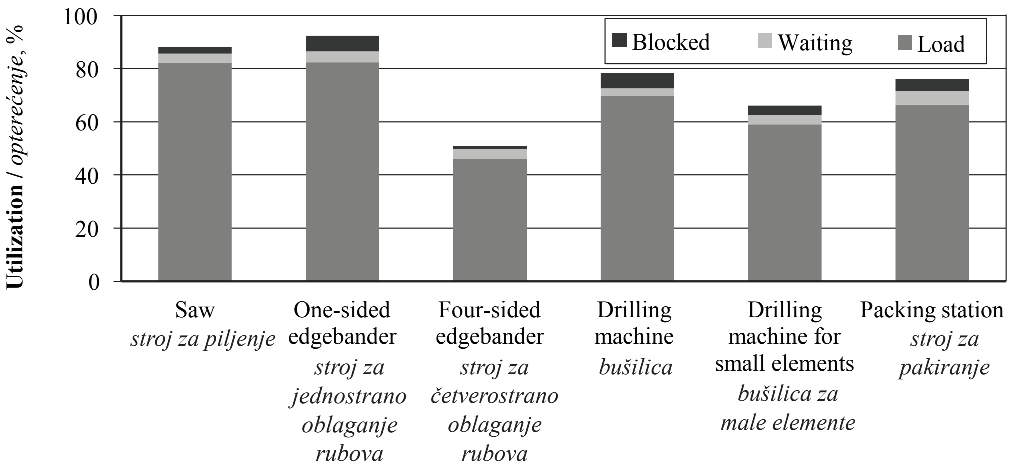


**Figure 7** Loads of machines and facilities
**Slika 7.** Opterećenost strojeva i opreme

the use of ANN and manufacture of the other group will be based on a sequential pull system. The presented results confirm the rightness of the suggested approach to demand forecasting on the basis of ANNs executing regressive relationships, where the forecast values calculated in traditional ways are included in the set of explanatory variables (hybrid approach). Effective forecasts based on ANNs (in comparison to those determined by traditional methods) make a basis for designing a replenishment pull system. Inventories of furniture parts planned according to the pull system principles, located in proper places in the manufacturing system and in proper quantity, not only speed-up the response for the customer's needs but also significantly increase productivity. Thanks to the implemented pull system, excessive stock levels resulting, among others, from wrong forecasts, are eliminated. This compensation is realized by the additional production line introduced for unpredictable and customized orders, working on the basis of a sequential pull system. Moreover, implementation of the simulation model makes it possible to verify the number of wood-processing machines and to execute the assumed furniture production plan on the grounds of the $i_0$ value. Such a complex approach to planning and controlling production systems in furniture companies will provide them with an opportunity to become more efficient, agiler and flexible on the market.

## **Appendix** – Dodatak

**Table 3** Initial research results
**Tablica 3.** Inicijalni rezultati istraživanja

| **Product** *Proizvod* | A | | | B | | | C | | | D | | | E | | | F | | | N | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Forecasting method** / *Metoda predviđanja* | SES | MA | ANN | SES | MA | ANN | SES | MA | ANN | SES | MA | ANN | SES | MA | ANN | SES | MA | ANN | SES | MA | ANN |
| **Relative Forecast Error ex-post, %** *Relativna pogreška predviđanja, %* | 128 | 114 | 60 | 136 | 105 | 101 | 131 | 108 | 95 | 130 | 113 | 86 | 135 | 124 | 111 | 125 | 108 | 95 | 140 | 117 | 100 |
| **Correlation coefficient** *Koeficijent korelacije* | 0.06 | -0.05 | 0.77 | 0.00 | -0.01 | 0.02 | 0.08 | -0.03 | 0.35 | 0.08 | 0.01 | 0.47 | 0.07 | -0.01 | -0.02 | 0.13 | 0.11 | 0.30 | -0.03 | -0.04 | 0.20 |

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