APEM journal
Advances in Production Engineering & Management
Volume 12 | Number 4 | December 2017 | pp 337–352
https://doi.org/10.14743/apem2017.4.262
ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

Improving workforce scheduling using artificial neural networks model

Simeunović, N.[a], Kamenko, I.[a], Bugarski, V.[a], Jovanović, M.[a], Lalić, B.[a,*]

[a]University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia

ABSTRACT

This paper demonstrates a decision support tool for workforce planning and scheduling. The research conducted in this study is oriented on batch type production typical for smaller production systems, workshops and service systems. The derived model in the research is based on historical data from Public utility service billing company. Model uses Artificial Neural Networks (ANN) fitting techniques. A set of eight input indicators is designed and two variants were tested in the model with two different outputs. Several comprehensive parameter setting experiments were performed to improve prediction performances. Real case studies using historic data from public weather database and communal consolidated billing service show that it is difficult to predict the required number of servers-workers in front office. In a similar way, this model is adequate for complex production systems with unpredictable and volatile demand. Therefore, manufacturing systems which create short cycle products, typical for food processing industry, or production for inventory, may benefit of the research presented in this paper. ANN simulation model with its unique set of features and chosen set of training parameters illustrate that presented model may serve as a valuable decision support system in workforce scheduling for service and production systems.

ARTICLE INFO

Keywords:
Workforce scheduling
Production planning
ANN prediction
Operations management

**Corresponding author:*
blalic@uns.ac.rs
(Lalić, B.)

Article history:
Received 6 June 2017
Revised 15 September 2017
Accepted 8 November 2017

1. Introduction

In recent years artificial intelligence is increasingly used to solve optimisation problems in scheduling or timetabling [1]. The skilled Workforce Project Scheduling is a complex problem of resource assignments and task scheduling that are performed on daily bases in service centres [2]. Internal, as well as external, part of the service processes has to be performed as a whole with planned level of quality and efficiency. The aim of the paper is to demonstrate an example of workforce planning and scheduling, predicting the need of products and services, which has direct implication on operation manager's tasks such as: production process planning, design and management, logistics management, quality management and productivity improvement[3]. Chopra *et al.* defines the area of operational management as a planning and management of transformation processes which contribute to creation of social value [4]. Previous statements demonstrate that there is no strict limitation between production and service delivery [3], but is clear that efficient management of organizational resources have a positive effect on successfully reaching organizational goals.

Services are intangible and customers participate actively or passively in the service delivery process [5]. Waiting is inevitable in any service delivery process that involves some type of randomness like random arrival. Workforce management (WFM) systems are automated tools which allow workforce to be managed more effectively and efficiently [6].Workforce management systems may be observed as an IT systems driving the organizational innovation in workforce scheduling [7]. Workforce management tools enable the capability of the Company to increase the level of the productivity [8].

Experience based workforce scheduling is the simplest way of planning. In order to achieve flexibility and high responsiveness towards the client needs, different ways of planning methods and use of real time data may be used to improve the service process. Rather than solely plan driven approach, creating monthly or bi-annual plans of workforce scheduling, iterative and real time planning could be used as an alternative. Iterative planning is implemented through shorter iteration cycles (daily or weekly planning) and it requires a decision support system based on the real time data, predicting the estimation of the number of the clients to be attended by the production or service system, which is at the same time designed with satisfactory error level. Therefore, to able to plan more efficiently, and to be able to respond to unexpected changes in service demand, decision support tool should be developed and customized according to the Company needs. One way of achieving the solution for this problem is to develop Artificial Neural Network (ANN) prediction model to be used by workforce project scheduling manager.

Majority of demand prediction issues, especially in production systems oriented on lean approach and Just in Time (JIT) concept, may be resolved if the model proposed in this research would be used. Inputs for this kind of model may be multiple variables such as product demand, consumer income, product price range etc. These variables directly influence and should be incorporated in algorithm for product demand prediction. In this research study the focus is on product and service prediction which depend on seasonal parameters – weather condition. The model may be successfully used to reduce early risks in supply chain management. Early risks and uncertainties exists in demand prediction, capacity planning, time delivery estimation, and production cost estimation [9].

This study is motivated by the challenge to predict as accurately as possible the number of required servers in Public Billing Service Company, using weather forecast and historical transactions data, underlying on methodology of ANN. By predicting the expected number of servers on daily bases, management of the Company can direct and transfer employees from back-end to front-end office and vice versa. In this manner, operational efficiency would be improved and employees would be working with clients in the front-end office, or would be directed to the background activities.

The research objective of this paper was to explore if appropriate neural network decision support system could be developed for the needs of Public Utility Company billing department. Use of WFM system in a supermarket chain is presented by Mirrazavi and Beringer [10], and in their work system allowing the demand to be precisely estimated. Aicklein and Dowsland [1] used genetic algorithms for resolving scheduling problems in medical industry. Their intention was to develop a fast and flexible solution to nurse scheduling problem. Group of authors presented a hybrid genetic algorithm for solving scheduling problem in service centers with genetic algorithm as a decision support tool [2]. Application of Particle Swarm Optimization algorithm for scheduling of home care workers in UK showed promising results in terms of effective and efficient scheduling of employees [11]. Support Vector Machine may be used well to predict thermal comfort of visitors in public areas, and group of authors showed that certain climate factors can be well related to predict the comfort of visitors [12]. Rebai *et al.* [13] considered a problem of scheduling production jobs on parallel machines in production, and have minimized the job completion time with genetic algorithms. Nissen and Günther [14] also used Particle Swarm Optimization algorithm for day to day workforce scheduling, as the way to improve productivity. Workforce scheduling is very important part of operations management and a crucial for a good organization management [15]. As the reports suggest, in Germany (which is considered highly productive country) employees spend up to 36 % of their work time unproductively, depending on the branch [16]. In most cases the usual tools for planning are prior experience and spreadsheets [17]. Different decisions support models for the workforce scheduling are identified in the research literature but due to specificity of the observed system of the Public Utility Company billing process it was necessary to develop a new customized solution to be used for this case.

Literature review

This section summarizes previous work scientific literature in the fields of: production and service systems, workforce scheduling and advanced technologies in workforce scheduling.

Production and service systems

In this paper we discuss workforce capacity management and operational distribution of the workforce in service and production systems. According the Schroeder production systems may be classified by the process type on: line systems, batch and project oriented production [18]. The research conducted in this study is oriented on batch type production which is typical for smaller production systems and workshops. Over the years there was a disagreement weather the service is a product or not and what is the difference between service and products [19]. According to the ISO 9001:2015 standard [20] service is defined as one of the four types of products, and their main characteristics are defined also. First characteristic is that service is intangible [21], although some authors tend to disagree with this [22]. Second characteristic is that services cannot be stock piled. Third characteristic states that it is impossible to separate the client getting the service and the service itself. Fourth characteristic is involvement of the client in the service process or the making of the service. Fifth characteristic is referred to as a service level quality in this paper, and it states that services are perishable goods, and they don't tolerate waiting [21]. If the service is received latter then expected the client will rate its quality lower, even if everything else was on the level that was expected by the client [23]. The quality of the service is correlated with the moment when the service is delivered [24]. Creating service experience-point of service starts at the first moment when the client gets in touch with service provider, interior of the place where service is provided, rules and terms of engagement [25], [26]. Numerous factors influence service experience such as interaction with employees [27], psychology and behavior of distribution personnel in direct contact with customers [28], and client waiting time in queue for the service [29].

Workforce scheduling

The impact of workforce scheduling system is very severe in terms of both quality of the service, and productivity [6], and not having a workforce scheduling system can be potentially disastrous for the company. In the transitional economies where Public Utility Companies are still self-centred instead of being client-centred, the inefficiency will signal for competition from private sector [30]. While having an workforce scheduling system based on experience can be appropriate prediction tool until certain extent, there are obviously limitations in terms of system size and ever-changing client demands [8]. Billing companies by the nature of their work have a negative connotation for the clients, service productivity should be in focus, while also having in mind clients waiting time [7]. Also there should be not worries about dip in productivity while rotation [31] as both front-end office and back-end office are equally demanding [2]. As with other service companies the key to successful work scheduling system is the prediction of client numbers [8] for each day in advance, and this is where artificial neural networks can help.

Advanced technologies in workforce scheduling

Soft computing methods such as artificial neural networks (ANN) have been successfully used for forecasting and decision-making [32]. In service systems, ANN have been applied mostly in simulation models [33]. Altiparmaket *at al.* [34] presented advantages of ANN metamodeling approach in modelling of asynchronous assembly systems. One good example of ANN application in predicting the accumulation of clients is published in [35] where ANN is used for forecasting patient length of stay in an emergency department. Not many cases of artificial neural networks (ANN) used as a decision support tool for short term planning in service systems can be found in research literature. Most of the research has been done in the field of medicine, specifically emergency medicine, where ANN was used to determine the length of stay of patients in emergency departments. The model shows around 80 % of accuracy with 5 predictors. Gul *at al*. [35] also used ANN as a tool for predicting patient length of stay at intensive care. Candan *at al*. [36] used neuro-fuzzy ANN to create model that they used to predict demand in pharmaceutical industry. Milović *at al*. [37] used data mining to create decision support tool for hospital management. Different methods have been used for workforce scheduling such as PSO-based algorithm [11], indirect genetic algorithm [1], genetic algorithm [38] and others [8]. Other researchers used discreet event simulation model for capacity planning in emergency medical departments [39], [40]. All these researches create a prediction tool used for different goals like queue management, capacity management and workforce scheduling and rotation.

The rest of the paper is organized into seven sections. Section 2 defines the problem. Section 3 presents prior related research. Section 4 describes the research data. Section 5 discusses the ANN prediction model. In Section 6, the empirical results are summarized and discussed. Section 7 contains the concluding remarks and future work. Finally, references are listed in Section 8.

2. Problem definition

The problem to be tackled in this paper can be described as follows. The task is to create weekly schedule with daily updates if significant changes in input parameters are identified. The proposed schedule has to satisfy employee contracts and meet the forecasted demand of clients to be served by the Public Utility Company billing system. In other words, internal optimization of the systems (shifting employees between front-end and back-end office) should not decrease the expected service level quality measured by waiting time of the client, on the contrary, the service level quality level should be increased from the perspective of the client. When operating performance improved, sooner or later results are converted into profits [41]. In the Fig. 1 billing service process in the Public Utility Company is shown.

Scheduling manager should plan in the most efficient way the distribution of employees between the front-end office and back-end office. As the bills usually arrive in the first week of the month, the company can expect the most of the clients coming to their office to pay the bills at that time, and based on workers' previous experience workforce scheduling was planned based on this parameter. Bills are sent out on 6th or 7th of the month and majority of clients are expected to arrive in the front office around 15th of the month, therefore during those days' extra workers are allocated to the front-end office. However, many factors affect the behavior of clients coming to the front office to pay their bills. For instance, weather conditions, holidays, days of the week, are some of the most important factors affecting the clients. Research objective of this paper is to create a decision support tool, the artificial neural network system that would be able to predict the precise number of clients on daily bases (with acceptable error level) to be served in the billing process of Public Utility Company.

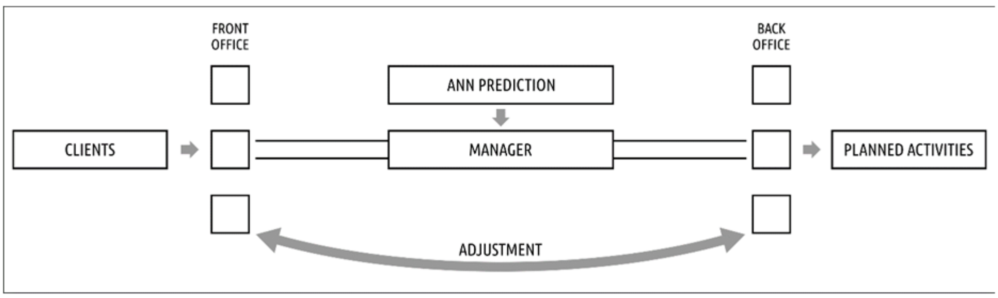

Fig. 1 Billing service process in the Company

Research data

This section presents the volume and origin of the research data and describes the selection of useful indicators for accurate prediction. The research data used in this study include publicly available daily weather information and historical transaction data from a Public Service Billing Company in period of one year (Fig. 2). The total number of cases is 393 days during one-year

Table 1 Classification of the research data set

Subset	Time period (YYYY-MM-DD)	Number of days (samples) Full working time	Reduced working time	Nonworking day	Total	Percentage
Training	2015-05-04 to 2016-03-31	235	45	52	332	84.48
Validation	2016-04-01 to 2016-05-08	22	5	11	38	9.67
Test	2016-05-09 to 2016-05-31	17	3	3	23	5.85
Total	2015-05-04 to 2016-05-31	274	53	66	393	100

period (from May 4 2015 to May 31 2016). Data set is classified on subsets (training, validation and test) and on type of working days in Table 1. The Public Billing Service Company operate in full working time (12.5 h) from Monday to Friday, in reduced working time (7 h) on Saturdays, while Sundays and National holidays are nonworking days.

From Fig. 2 it can be concluded that from there are very high oscillation on daily bases in number of transactions. Number of transactions per day ranges from to 245 to 4657 transactions per day. A lot of external factor affect the number of customers, and number of transactions in an observed day. The most influencing factor are weather conditions (rainfalls, very high and very low temperatures, thunderstorms etc.). The factor that has also very high influence is day in week, and day in month because payment deadline for communal bills is 20th in month, and during that period peak in number of customers can be expected. Training subset is presented to the network during training, and the network parameters are adjusted according to its error.

Validation subset is used to measure network generalization, and to halt training when generalization stops improving. Test subset has no effect on training and so provide an independent measure of network performance after training.

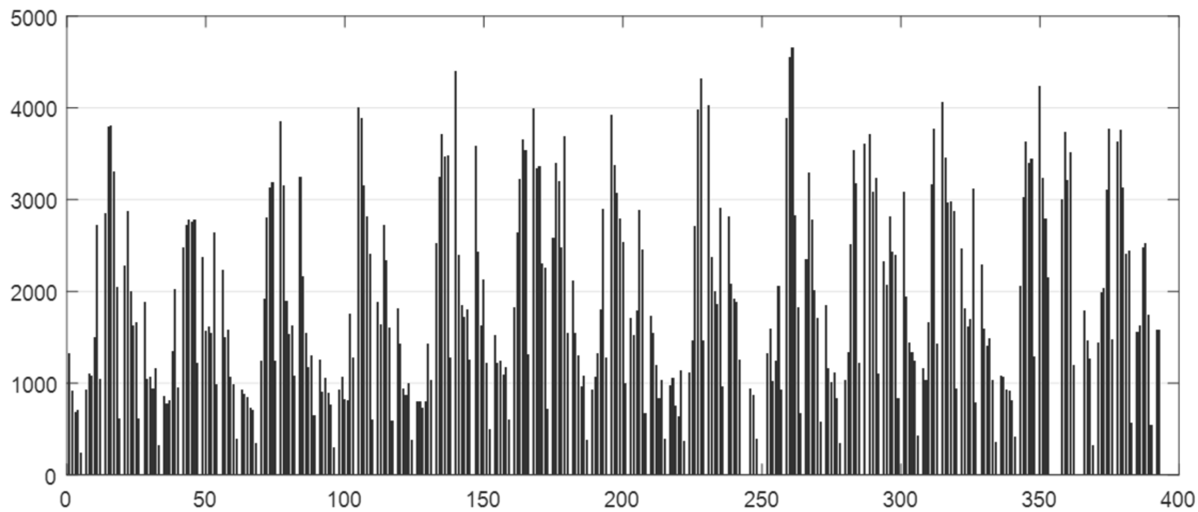

Fig. 2 Number of transactions per day

Weather data

The weather conditions data are downloaded from the public historic weather data database. Data is derived from the nearest weather station for the same date range that fits date range used for number of transactions. Data of interests are temperature, relative humidity, pressureat sea level, wind speed and current weather events.

Data are measured eight times per day. Data about temperature, relative humidity, pressure at sea level and wind speed are averaged over working time for the day of interest. For weather event that describes observed day, the worst measured event is adopted.

Indicators

Indicators are calculated based on the number of transactions and weather conditions data. Indicators on the better way represent and emphasis characteristic of real data. Average number of transactions per day during week

$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} TranNum_{i=j} \tag{1}$$

where j is an observed day in week, i is a current day in week and $TranNum_{i=j}$ is vector made up of m data samples of number of transactions where the current day in week is equals to the observed day in week.

Average number of transactions per day in month is calculated by Eq. 1 where j is an observed day in month, i is a current day in month and $TranNum_{i=j}$ is vector made up of m data samples of number of transactions where the current day in month is equals to the observed day in month.

Temperature index is calculated based on tree following equations that are proposed in [42]:

$$tempIndex = \begin{cases} 10 - heatIndex & T > 27 \\ 10 & 10 \leq T \leq 27 \\ 10 - windChill & T < 10 \end{cases} \tag{2}$$

$$\begin{aligned} heatIndex = {} & -8.78 + 1.61T + 2.34H - 0.15\mathrm{TH} - 1.23 \cdot 10^{-2}\mathrm{T}^2 - 1.64 \cdot 10^{-2}H^2 \\ & + 2.21 \cdot 10^{-3}HT^2 + 7.25 \cdot 10^{-4}TH^2 - 3.58 \cdot 10^{-6}T^2H^2 \end{aligned} \tag{3}$$

$$windChill = 13.13 + 0.62T - 13.95W_s^{0.16} + 0.486TW_s^{0.16} \tag{4}$$

where T is a temperature, H is a humidity and W_s is a wind speed.

Humidity index is calculated from relative humidity based on following equation.

$$humidityIndex = \begin{cases} H & P_{SL} < 40 \\ 40 & 40 \leq P_{SL} \leq 60 \\ 100 - H & T > 60 \end{cases} \tag{5}$$

Graphic representation of Eq. 5 is shown on Fig. 3:

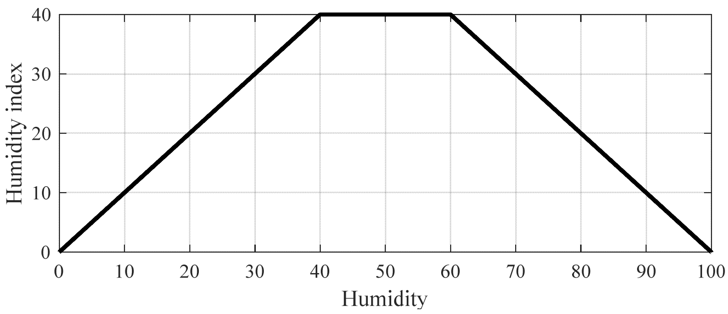

Fig. 3 Humidity index

Pressure index is calculated from pressure at sea level based on following equation:

$$pressureIndex = \begin{cases} 15 & P_{SL} > 1013.25 \\ P_{SL} - 1013.25 & 998.25 \leq P_{SL} \leq 1013.25 \\ 0 & T < 998.25 \end{cases} \tag{6}$$

Weather conditions are gradually coded starting with 1 representing the worst conditions (thunderstorms and rain) ending with 40 representing the good weather conditions (clear). Table 2 displays codes for particular weather conditions.

Table 2 Weather condition coding

Weather condition	Code
Thunderstorms and rain	1
Thunderstorm	2
Light thunderstorm	3
Light sandstorm	4
Light freezing rain	5
Heavy fog	6
Rain	10
Light rain showers	11
Light rain	12
Snow	13
Light snow	14
Light drizzle	15
Partial fog	20
Light fog	21
Mist	22
Overcast	30
Mostly Cloudy	31
Partly Cloudy	32
Scattered Clouds	33
Clear	40

Statistical parameters

Statistical parameters are calculated for all indicators and are presented in the Table 3.

Table 3 Statistical parameters of research data

Name of indicator	Min.	Max.	Mean	Std. dev.	Kurtosis	Skewness
Working hours	7.00	12.50	11.61	2.03	4.36	-1.83
Avg. trans. per day in week	812.51	2,276.34	1,886.60	481.54	4.12	-1.69
Avg. trans. per day in month	825.55	3,208.82	1,886.60	744.05	1.91	0.20
Temp. index	0.00	10.00	8.14	2.79	2.97	-1.18
Humidity index	1.00	40.00	29.29	11.12	2.25	-0.73
Pressure index	0.00	15.00	13.48	3.03	9.71	-2.57
Wind speed	0.72	32.40	8.31	5.17	5.83	1.52
Weather conditions	11.80	50.00	30.41	7.95	2.66	-0.24
Number of transactions	245.00	4,657.00	1,886.60	1,044.19	2.28	0.56
Number of servers	1.00	7.00	3.41	1.46	2.27	0.48

Mean value is calculated based on equation:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} I_i \tag{7}$$

where I is vector made up of n data samples of observed indicator.

Standard deviation is calculated based on equation:

$$\sigma = \frac{1}{n}\sqrt{\frac{1}{n-1}\sum_{i=1}^{n} |I_i - \mu|^2} \tag{8}$$

where I is vector made up of n data samples of observed indicator and μ is mean value of I.

Kurtosis is a measure of how outlier-prone a distribution is and is calculated based on equation:

$$k = \frac{E(I-\mu)^4}{\sigma^4} \tag{9}$$

Skewness is a measure of the asymmetry of the data around the sample mean and is calculated based on equation:

$$S = \frac{E(I-\mu)^3}{\sigma^3} \tag{10}$$

In both equations (Eq. 9 and 10) I represents vector made up of n data samples of observed indicator, μ is mean value of I, σ is standard deviation of I and $E(t)$ represents the expected value of the quantity t.

3. ANN prediction model

Neuron is the basic process element of ANN. Model of one neuron can be seen in Fig. 4. Generally speaking neuron has n inputs labeled with x_i $(i = 1,2,3,\dots,n)$ that represents source of input signal. Every inputs are weighted with w_i before reach the body of process element. In process element all weighted inputs and bias w_0 are summarized. Activation signal R_i gets a value of summation if a sum is greater than threshold θ_i otherwise activation signal becomes zero. Activation signal R_i further leads to nonlinear function f_i. The output of nonlinear function is the output of neuron O_i. The functional depending from input to output for one neuron is given in following equation:

$$\begin{gathered} O_i = f_i\left(\sum_{j=1}^{n} w_{ij}x_{ij} + w_0\right) \\ \sum_{j=1}^{n} w_{ij}x_{ij} + w_0 \geq \theta_i \end{gathered} \tag{11}$$

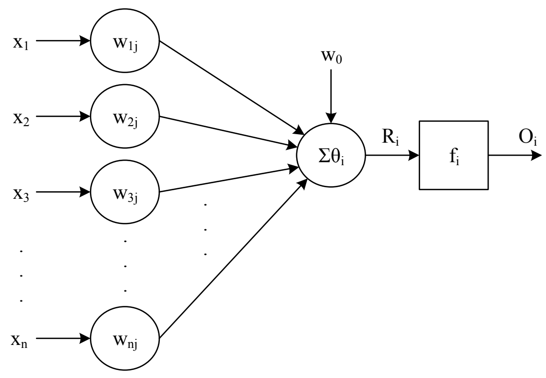

Fig. 4 A model of one neuron

In this research, two-layer feed-forward Artificial Neural Network with sigmoid hidden neurons (white circles in Fig. 6) and linear output neurons (gray circles in Fig. 6) is composed for prediction of required number of servers in billing service. Network inputs are carefully designed as eight indicators with greatest impact on prediction performance.

Two different training sets are created for ANN training experiments. First training set is created to train the network to predict the number of transactions, from which is later calculated the number of required servers. This calculation takes into consideration the number of working hours (the next working day) and statistical average number of transactions per server. One server can process up to 55 transactions per hour. Statistical average number of transactions per server is calculated as 688 (55 × 12.5) transactions for full working time (12.5 h) and 385 (55 × 7) transactions for reduced working time (7 h). The correlation between number of transactions and number of servers is given in following equation:

$$ServNum = \begin{cases} 1, & 1 \leq TranNum \leq 688\ (385) \\ 2, & 689\ (386) \leq TranNum \leq 1375\ (770) \\ 3, & 1376\ (771) \leq TranNum \leq 2063\ (1155) \\ 4, & 2064\ (1156) \leq TranNum \leq 2750\ (1540) \\ 5, & 2751\ (1541) \leq TranNum \leq 3438\ (1925) \\ 6, & 3439\ (1926) \leq TranNum \leq 4125\ (2310) \\ 7, & 4126\ (2311) \leq TranNum \leq 4813\ (2695) \end{cases} \tag{12}$$

where $ServNum$ is calculated number of servers and $TranNum$ is number of transactions. Graphical representation of this equation is shown in Fig. 5. In brackets is given number of transactions for day with reduced working time (Saturdays).

The second idea was to train the network to predict the number of required servers directly. For that case, desired output column of training set was recalculated using Eq. 11.

The architecture of the prediction model is illustrated in Fig. 6. The number of neurons in hidden layer is determined empirically. The output layer consists of just one neuron with a purpose to return the predicted number of transactions that will occur next day. Prediction model uses the output of the ANN to calculate the required number of servers for the next working day.

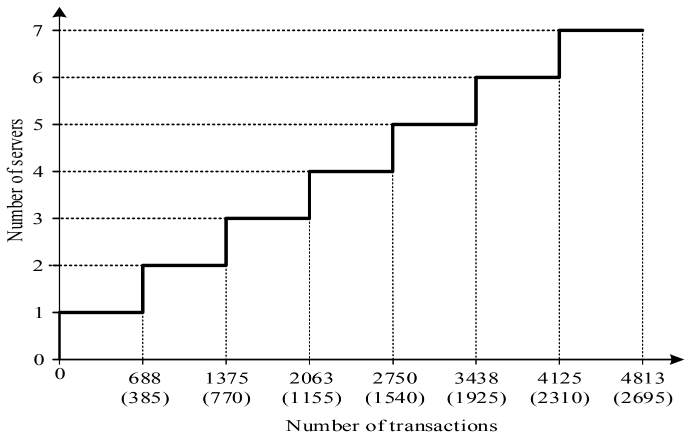

Fig. 5 Ceiling function

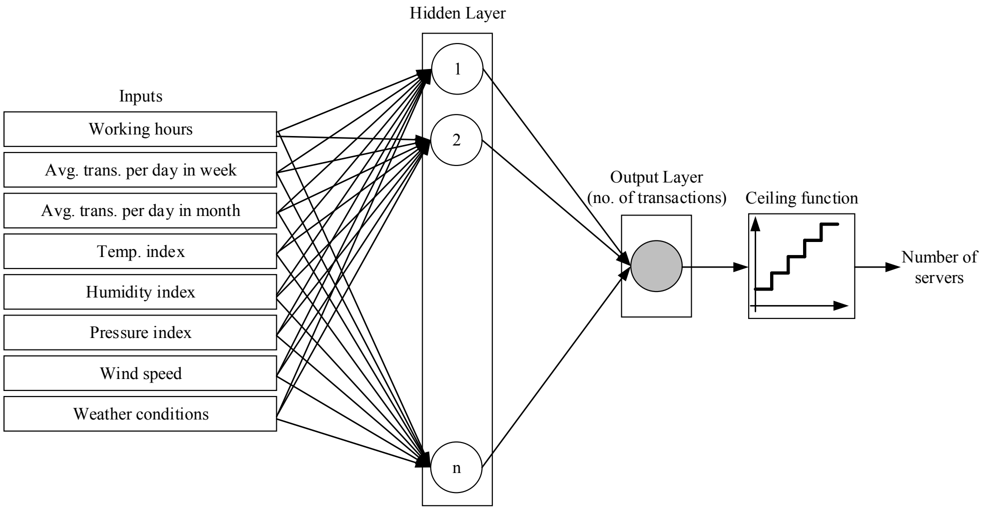

Fig. 6 The architecture of prediction model

The backpropagation learning algorithm was used for training the proposed ANN. Three different training functions Levenberg-Marquard, Bayesian regularization and Scaled conjugate gradient algorithm. Levenberg-Marquard algorithm typically requires more memory but consume less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. One example of convergence graph can be seen in Fig. 7. Bayesian regularization typically requires more time, but can result in good generalization for difficult, small or noisy datasets. Training stops according to adaptive weight minimization (regularization). Scaled conjugate gradient algorithm requires less memory. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

Fifty-one different values of neurons in hidden layer (n) were tested for both training sets. Number of neurons is ranging from 8 to 58 neurons in experiments. ANN has 8 inputs and it is not recommended to use number of neurons in hidden layer smaller than number of inputs. Also very large number of neurons often leads to network overfitting and can be time consuming during training process. Training was repeated thirty times for each combination of parameters (2 training sets, 3 training functions and 51 different number of neurons in hidden layer). That yield 9.180 (2 × 3 × 51 × 30) treatments for ANN. The best training function, the most appropriate number of neurons in hidden layer and the best combination of both are determined in these experiments. Table 4 summarizes ANN parameters and their values used in experiments.

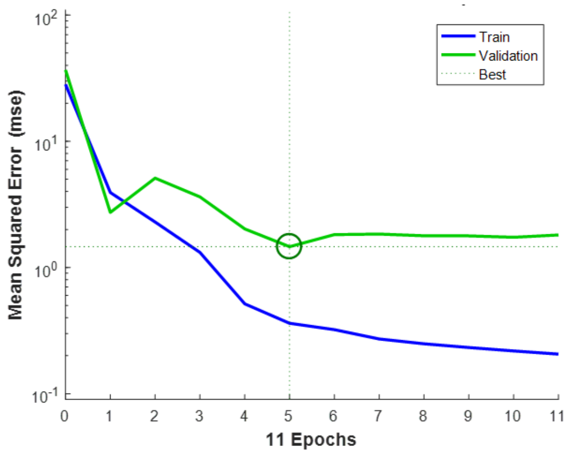

Fig. 7 Convergence graph

Table 4 ANN parameter values tested in experiments

Parameters	Level(s)
Backpropagation training function	Levenberg-Marquard, Bayesian regulation, Scaled conjugate gradient
Number of neurons in hidden layer	8, 9, 10, ... , 58
Maximum number of epochs to train	1000
Maximum validation failures	6
Minimum performance gradient	1e-6
Performance goal	0

4. Results and discussion

The aim of this study was to demonstrate a decision support tool for Public Billing Service company that would help them schedule the workforce with better accuracy, leaving them time for planning work in the back office. The presented prediction tool is intended to be used by the company to improve the operational efficiency with rotation of employees between back-end and front-end while both improving the workforce efficiency and service experience for the customers. We've presented decision support system that is based on the predictions made by artificial neural networks that take in account different variables and put out a number of servers needed (workers in front office) for the day ahead. It is suitable for single or small batch production for products that cannot be stored for a long time (such as food), and demand prediction is very important for these systems. Each product or line of products is produced in a different manner. Advantage of batch production is its flexibility to accommodate specific requests of customers. In this production type products are frequently changed and tasks for workforce are varying significantly. Different simulation models used in production systems are customized for service management and vice versa. McDonald's Company, or similar fast food production systems where food is prepared in the back office in accordance with all the organization principles in industrial production may serve as a good example of production and service systems analogy. Similarly, workshop for pastry and ice cream production where product offer directly depends on weather circumstances. Workforce in this production type have to be more qualified than workforce in line production systems, which increases labour costs and total cost of production process. Due to this reason, well performed demand estimation is very important to distribute resources in production process. Artificial intelligence and neural networks application brings better consumer behaviour estimation. By using the proposed model, demand planning and production process improvement and optimization is expected.

The major contributions of this study was to explore, demonstrate and verify the predictability of required number of servers (front office workers) for the next working day in real billing service institution in Novi Sad (Serbia). Using historical and forecast data, the proposed methodology gives very encouraging results. The number of required servers, which in real cases varied from one to seven, is predicted exactly in most test cases, while the worst cases were very rare and with maximal error of two servers. This effectiveness proved that presented ANN model could be a valuable decision support in workforce scheduling system. With the help of the prediction tool, employees in billing department can be assigned with proper tasks (in front-end or back-end) resulting with increased productivity.

For ANN trained with first training set, mean error between target (real) and output (predicted) number of transactions is shown on Fig. 8. For the same ANN mean error between target (real) and output (predicted) number of servers expressed through number of transactions is shown on Fig. 9. On both figures (Fig. 8 and Fig. 9) error obtained with Levenberg-Marquard algorithm is displayed with dash-dotted line, error achieved with Bayesian regularization algorithm is displayed with dashed line and error achieved with Scaled conjugate gradient algorithm is displayed with dotted line. Best mean error in number of transactions is obtained when ANN with 26 neurons is trained with Bayesian regularization algorithm. In that case mean error was 429.17 transactions. When number of transactions is expressed in number of servers best mean error is achieved when ANN with 21 neurons is trained with Bayesian regularization algorithm. In that case mean error has value 0.55 servers.

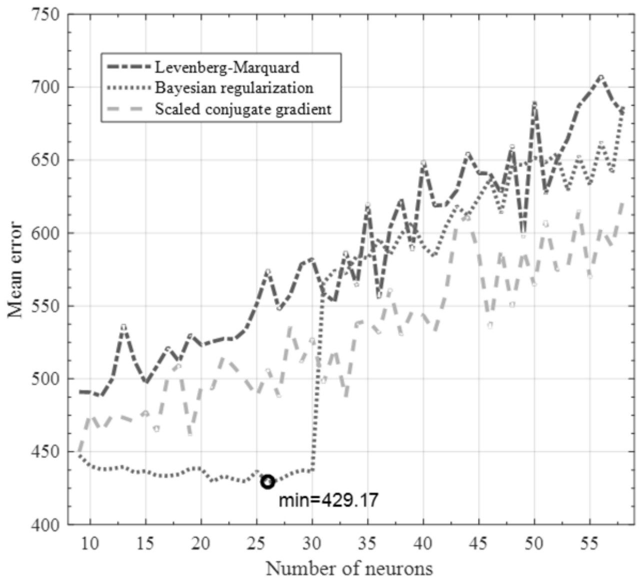

Fig. 8 Mean error between target and output number of transactions for first training set

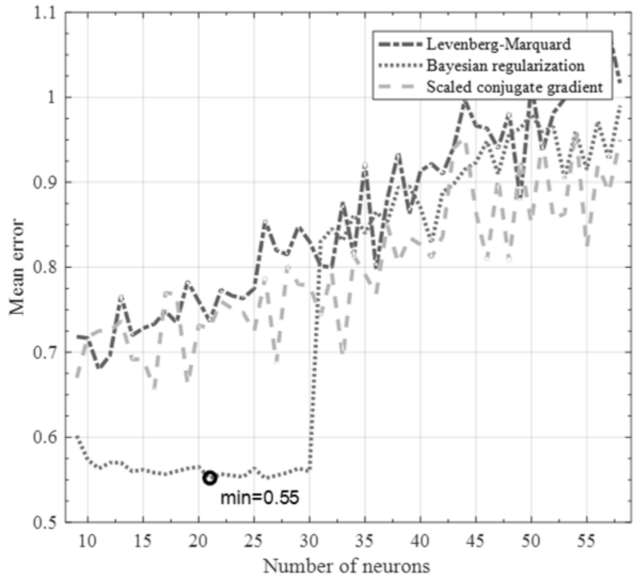

Fig. 9 Mean error between target and output number of servers for first training set

For ANN trained with second training set mean error between target (real) and output (predicted) number of servers is shown on Fig. 10. Error obtained with Levenberg-Marquard algorithm is displayed with dash-dotted line, error achieved with Bayesian regularization algorithm is displayed with dashed line and error achieved with Scaled conjugate gradient algorithm is displayed with dotted line. Best mean error in number of servers is obtained when ANN with 43 neurons is trained with Bayesian regularization algorithm. In that case mean error has value 0.83 servers.

For ANN trained with first training set, minimum error in number of transactions is obtained with 17 neurons and Scaled conjugate gradient algorithm, Fig. 11(a). In that case mean error was 295.87 transactions, Fig. 11(b). For the same ANN minimum error in number of servers is obtained with 14 neurons and Scaled conjugate gradient algorithm, Fig. 11(c). In that case mean error was 0.3 servers, Fig. 11(d).

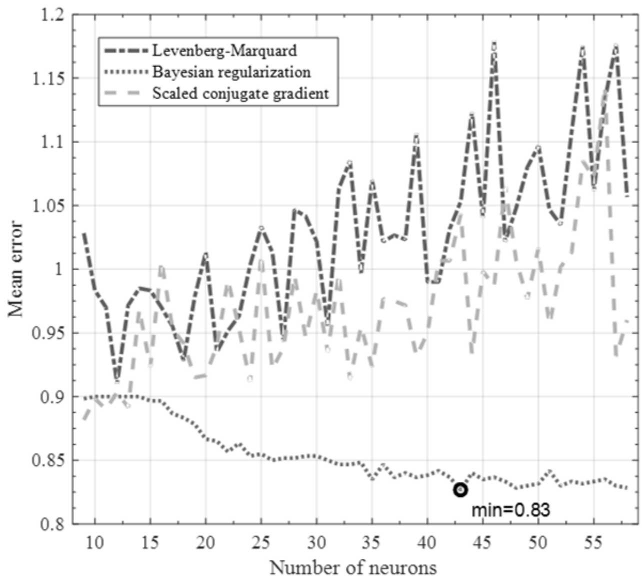

Fig. 10 Mean error between target and output number of servers for second training set

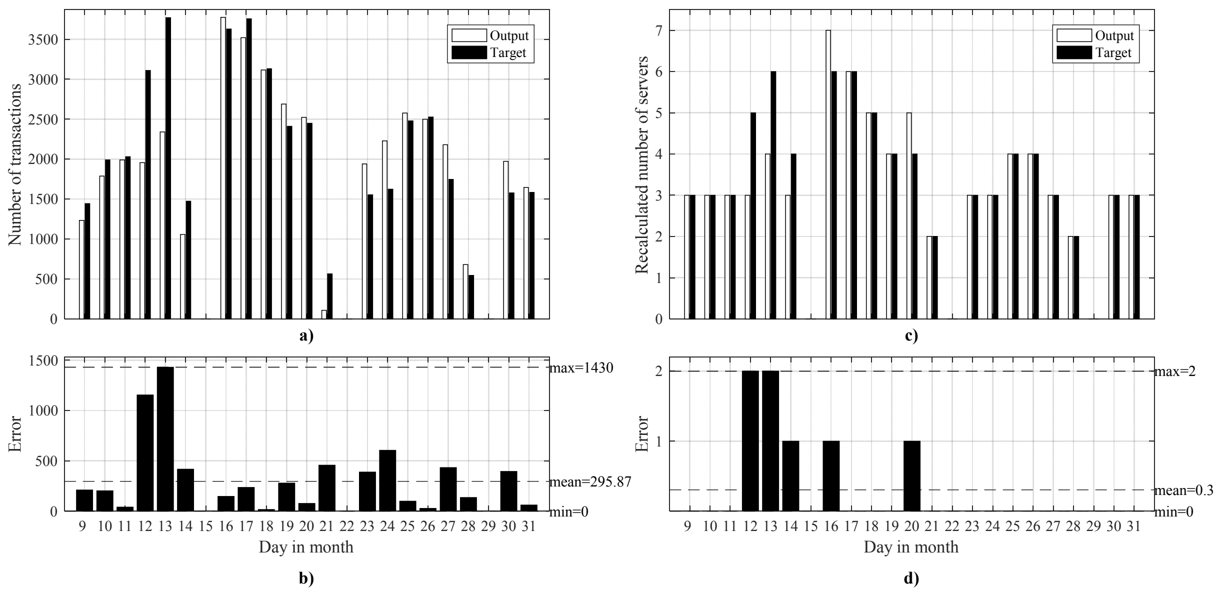

Fig. 11 Target and output number of transactions for first training set (a), error between them (b), target and output number of servers for first training set (c), error between them (d)

For ANN trained with second training set, minimum error in number of servers is obtained with 28 neurons and Levenberg-Marquard algorithm, Fig. 12(a). In that case mean error was 0.57 servers, Fig. 12(b).

In Table 5 is presented summarized view of obtained errors for ANN tested with train and test subset of both training set.

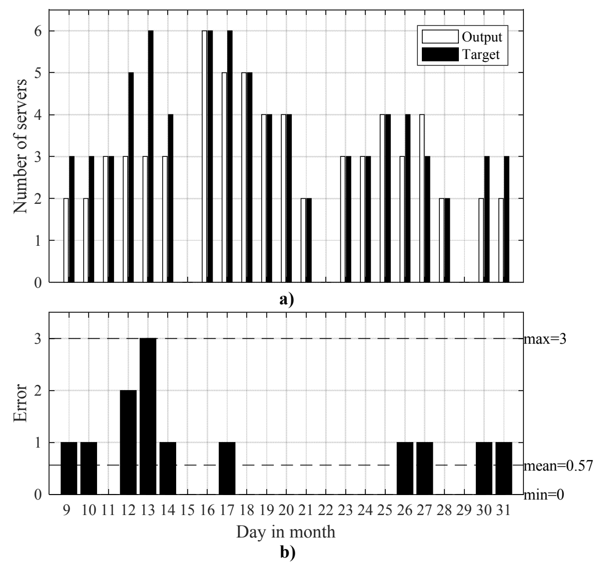

Fig. 12 Target and output number of servers for second training set (a), error between them (b)

Table 5 Results review

Training set	Min	Max	Mean	Err = 0 (%)	Err = 1 (%)	Err > 2 (%)
First training set (training subset)	0.00	2.00	0.12	88.34	11.38	0.28
First training set (test subset)	0.00	2.00	0.30	78.26	13.05	8.69
Second training set (training subset)	0.00	3.00	0.18	84.28	13.82	1.90
Second training set (test subset)	0.00	3.00	0.57	56.52	34.79	8.69

4. Conclusion

In this paper we have presented a decision support tool to be used in Public Utility Service Company. Primary objective was to improve efficiency of workforce scheduling which was successfully achieved with use of prediction system. With use of presented decision support system management can plan workforce rotation and optimize both the front-end office workers and back-end office workers and synchronize activities. Another objective was to improve quality and reduce waiting times for clients, and with proper workforce scheduling there should be a minimum of ad-hoc situations demanding additional counter to reduce the waiting lines. ANN prediction model estimating number of expected clients on daily bases was key to achieving the predefined research objectives. Estimation error is satisfactory and proposed model could be applied in the real system with minor changes in the work system. By using the model presented in the paper, unpredictability can be reduced since ANN prediction model improves demand estimation, which helps in real time workforce distribution and thus reduces supply chain management risks.

Improving waiting times is one way of improving the customer service, and secondary focus of this research paper was on this parameter. Adequate and timely response have become a prerequisite for good business results in industrial production and service management. Due to frequent product or service demand changes it is important to be capable to adapt the rearrange distribution of machines/servers or workforce to accommodate the market expectations.As this is the Public Utility company case, the queuing policy is that there should always be minimum number of servers available. With that in mind, an average error of 0.3 servers per day would be major increase both in company's productivity in back-end office (primary focus) and in customer satisfaction due the minimized waiting time. In current working conditions, with minimum number of servers needed the waiting time is around 2.3 minutes, and the average error of 0.3 servers would not have significant impact on waiting time. However, having extra workers in the front-end office on less crowded days is not needed (frequent scenario with current workforce scheduling), and their assignment to the back-end office would greatly improve the operational efficiency. Data used in the ANN prediction model were historical daily transaction information on transactions and publicly available weather conditions during that period, summing up to 8 parameters in total.

In the future research additional historical data about transaction or influence of e-commerce should be taken into account. Improving other dimensions of the customer service (apart from reduction of waiting time which was focus of this research) should also be taken in account for future research. Adding the historical data of transactions would improve the ANN training. In this research one year of data was used, but with further data we could expect to reduce the error present in the current model due the nature of moving holidays (mainly religious holidays), that are specific for this region. As it was seen in the results, major error in the prediction model was tied to the case of moving holiday.

References

[1] Aickelin, U., Dowsland, K.A. (2004). An indirect genetic algorithm for a nurse-scheduling problem, *Computers & Operations Research*, Vol. 31, No. 5, 761-778, doi: 10.1016/S0305-0548(03)00034-0.

[2] Valls, V., Pérez, Á., Quintanilla, S. (2009). Skilled workforce scheduling in service centres, *European Journal of Operational Research*, Vol. 193, No. 3, 791-804, doi: 10.1016/j.ejor.2007.11.008.

[3] Bayraktar, E., Jothishankar, M.C., Tatoglu E., Wu, T. (2007). Evolution of operations management: Past, present and future, *Management Research News*, Vol. 30, No. 11, 843-871, doi: 10.1108/01409170710832278.

[4] Chopra, S., Lovejoy, W., Yano, C. (2004). Five decades of operations management and the prospects ahead, *Management Science*, Vol. 50, No. 1, 8-14, doi: 10.1287/mnsc.1030.0189.

[5] Sandmann, W. (2013). Quantitative fairness for assessing perceived service quality in queues, *Operational Research*, Vol. 13, No. 2, 153-186, doi: 10.1007/s12351-011-0111-9.

[6] Calabrese, A., Capece, G., Costa, R., Di Pillo, F., Paglia, D. (2013). The impact of workforce management systems on productivity and quality, *Knowledge and Process Management*, Vol. 20, No. 3, 177-184, doi: 10.1002/kpm.1417.

[7] Calabrese, A. (2012). Service productivity and service quality: A necessary trade-off?, *International Journal of Production Economics*, Vol. 135, No. 2, 800-812, doi: 10.1016/j.ijpe.2011.10.014.

[8] Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E., De Boeck, L. (2013). Personnel scheduling: A literature review, *European Journal of Operational Research*, Vol. 226, No. 3, 367-385, doi: 10.1016/j.ejor. 2012. 11.029.

[9] Taylor, D.L., Brunt, D. (2001). *Manufacturing operations and supply chain management: The LEAN approach*, Thomson Learning, London, UK.

[10] Mirrazavi, S.K., Beringer, H. (2007). A web-based workforce management system for Sainsburys supermarkets Ltd., *Annals of Operations Research*, Vol. 155, No. 1, 437-457, doi: 10.1007/s10479-007-0204-2.

[11] Akjiratikarl, C., Yenradee, P., Drake, P.R. (2007). PSO-based algorithm for home care worker scheduling in the UK, *Computers & Industrial Engineering*, Vol. 53, No. 4, 559-583, doi: 10.1016/j.cie.2007.06.002.

[12] Mladenović, I., Sokolov-Mladenović, S., Milovančević, M., Marković, D., Simeunović, N. (2016). Management and estimation of thermal comfort, carbon dioxide emission and economic growth by support vector machine, *Renewable and Sustainable Energy Reviews*, Vol. 64, 466-476, doi: 10.1016/j.rser.2016.06.034.

[13] Rebai, M., Kacem, I., Adjallah, K.H. (2000). Scheduling jobs and maintenance activities on parallel machines*, Operational Research,* Vol. 13, No. 3, 363-383, doi: 10.1007/s12351-012-0130-1.

[14] Nissen, V., Günther, M. (2009). Staff scheduling with particle swarm optimisation and evolution strategies, In: *EvoCOP, Evolutionary Computation in Combinatorial Optimization,* Tübingen, Germany, 228-239, doi: 10.1007/ 978-3-642-01009-5_20.

[15] Pinedo, M., Chao, X. (1998). *Operations scheduling with applications in manufacturing and services*, Irwin /McGraw-Hill, Boston, USA.

[16] Bakhrankova, K. (2008). Production planning in continuous process industries: Theoretical and optimization issues, In: *Operations Research Proceedings 2008,* University of Augsburg, Augsburg, Germany, 67-72.

[17] ATOSS Software AG, Standort Deutschland 2006: Zukunftssicherung durch intelligentes personal management, from: *https://www.atoss.com/en-gb/Workforce-Management*, accessed October 13th, 2016.

[18] Schroeder, R.G. (1989). *Operations management: Decision making in the operations function*, McGraw-Hill, New York, USA.

[19] Solomon, M.R., Surprenant, C., Czepiel, J.A., Gutman, E.G. (1985). A role theory perspective on dyadic interactions: The service encounter, *Journal of Marketing*, Vol. 49, No. 1, 99-111, doi: 10.2307/1251180.

[20] ISO – International Organization for Standardization, ISO 9000:2015, from: https://www.iso.org/standard/ 45481.html, accessed October 13th, 2016.

[21] Slack, N., Brandon-Jones, A., Johnston, R. (2014). *Operations Management, 7th Edition*, Pearson, London, UK.

[22] Vargo, S.L., Lusch, R.F. (2004) The four service marketing myths: Remnants of a goods-based manufacturing model, *Journal of Service Research*, Vol. 6, No. 4, 324-335, doi: 10.1177/1094670503262946.

[23] Tom, G., Lucey, S. (1995). Waiting time delays and customer satisfaction in supermarkets, *Journal of Services Marketing*, Vol. 9, No. 5, 20-29, doi: 10.1108/08876049510100281.

[24] Zemke, R. (2002). Managing the employee connection, *Managing Service Quality: An International Journal*, Vol. 12, No. 2, 73-76, doi: 10.1108/09604520210421374.

[25] Aaker, D.A., Biel, A.L. (1993). Converting image into equity, In: *Brand Equity & Advertising: Advertising's Role in Building Strong Brands*, Hillsdale, New York USA, 67-82.

[26] Kerin, R.A., Ambuj, J., Howard, D.J. (1992). Store shopping experience and consumer price-quality-value perceptions, *Journal of Retailing*, Vol. 68, No. 4, 376-397.

[27] Grace, D., O'Cass, A. (2004). Examining service experiences and post-consumption evaluations, *Journal of Services Marketing*, Vol. 18, No. 6, 450-461, doi: 10.1108/08876040410557230.

[28] Ren, X.Y., Kong, Z.F., Liang W.C., Li, H.C., Zhou, X.Y. (2017). Vehicle scheduling based on plant growth simulation algorithm and distribution staff behaviour, *Advances in Production Engineering & Management*, Vol. 12, No. 2, 173-184, doi: 10.14743/apem2017.2.249.

[29] Bielen, F., Demoulin, N. (2007). Waiting time influence on the satisfaction-loyalty relationship in services, *Managing Service Quality: An International Journal*, Vol. 17, No. 2, 174-193, doi: 10.1108/09604520710735182.

[30] Yang, Y., Hou, Y., Wang, Y. (2013). On the development of public-private partnerships in transitional economies: An explanatory framework, *Public Administration Review*, Vol. 73, No. 2, 301-310, doi: 10.1111/j.1540-6210. 2012.02672.x.

[31] Thompson, G.M., Goodale, J.C. (2006). Variable employee productivity in workforce scheduling, *European Journal of Operational Research*, Vol. 170, No. 2, 376-390, doi: 10.1016/j.ejor.2004.03.048.

[32] Hill, T., Marquez, L., O'Connor, M., Remus, W. (1994). Artificial neural network models for forecasting and decision making, *International Journal of Forecasting*, Vol. 10, No. 1, 5-15, doi: 10.1016/0169-2070(94)90045-0.

[33] Sundari. M.S., Palaniammal, S. (2015). Simulation of M/M/1 queuing system using ANN, *Malaya Journal of Matematik*, Vol. 3, No. 1, 279-294.

[34] Altiparmak, F., Dengiz, B., Bulgak, A.A. (2007). Buffer allocation and performance modeling in asynchronous assembly system operations: An artificial neural network metamodeling approach, *Applied Soft Computing*, Vol. 7, No. 3, 946-956, doi: 10.1016/j.asoc.2006.06.002.

[35] Gul, M., Guneri, A.F. (2015). Forecasting patient length of stay in an emergency department by artificial neural networks, *Journal of Aeronautics and Space Technologies,* Vol. 8, No. 2, 43-48, doi: 10.7603/s40690-015-0015-7.

[36] Candan, G., Taşkin, M.F., Yazgan, H.R. (2014). Demand forecasting in pharmaceutical industry using artificial intelligence: Neuro-fuzzy approach, *Journal of Military and Information Science*, Vol. 2, No. 2, 41-49.

[37] Milovic, B., Milovic M. (2012). Prediction and decision making in health care using data mining, *International Journal of Public Health Science,* Vol. 1, No. 2, 69-78, doi: 10.11591/ijphs.v1i2.1380.

[38] Asensio-Cuesta, S., Diego-Mas, J.A., Canós-Darós, L., Andrés-Romano, C. (2012). A genetic algorithm for the design of job rotation schedules considering ergonomic and competence criteria, *The International Journal of Advanced Manufacturing Technology,* Vol. 60, No. 9-12, 1161-1174, doi: 10.1007/s00170-011-3672-0.
[39] Carmen, R., Defraeye, M., Van Nieuwenhuyse, I. (2015). A decision support system for capacity planning in emergency departments, *International Journal of Simulation Modelling*, Vol. 14, No. 2, 299-312, doi: 10.2507/IJSIMM14(2)10.308.
[40] Baesler, F., Gatica, J., Correa, R. (2015). Simulation optimisation for operating room scheduling, *International Journal of Simulation Modelling*, Vol. 14, No. 2, 215-226, doi: 10.2507/IJSIMM14(2)3.287.
[41] García-Alcaraz, J.L., Maldonado-Macías, A.A., Alor-Hernández, G., Sánchez-Ramírez, C. (2017). The impact of information and communication technologies (ICT) on agility, operating, and economical performance of supply chain, *Advances in Production Engineering & Management*, Vol. 12, No. 1, 29-40, doi: 10.14743/apem2017.1.237.
[42] Oliver, J.E. (2005). *Encyclopedia of world climatology*, Springer, Dordrecht, The Netherlands.