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PREDICTION OF THE CHANGE IN NUMBER OF EMPLOYEES IN SERBIAN COMPANIES BASED ON CONTINGENCY AND QUALITY MANAGEMENT FACTORS

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Abstract: A company's development performance and growth may be impacted by a wide range of different factors, which unquestionably affect number of the employees in the loop. Taking into account all influencing factors, companies would benefit if have possibility to predict the degree of change in the number of employees in future period in order to adjust their internal strategy or to make appropriate decisions that enable the survival and progress of the company in the market. The aim of this research is to predict the change in number of employees based on current state of contingency and quality management factors, using information obtained from a survey of 67 different companies from Serbia. In the first part of the research, a correlation analysis is used with the aim to identify the specific contingency and quality management factors that are most closely associated to the subject of interest, which is, in this case, degree of change in the number of employes. The second part of the research involves feedforward neural network training for prediction of the degree of change in number of employees based on feature extraction of main factors. The training accuracy that proposed network achieved is 77.36%, while testing accuracy amounts 71.43%.

Keywords: Correlation analysis, feedforward neural networks, number of employees

1. INTRODUCTION

Risks are involved in almost all activities of a company, so the process of identifying, evaluating and managing risks is an essential component of the strategic development of a company and it has to be planned and designed at the highest level (Dionne, 2013). Risk management represents technique that prioritizes, controls and tracks all risks that may affect a company. Risk management is performed in order to minimize the probability of unfavourable events that can hurt a company or to maximize probability of the realization of positive opportunities (Sahu et al., 2014). There are many risk sources that should be considered in risk identification process. Numerous authors classified sources of risk to make them easier to recognize and track for certain types of industries. Akintoye and MacLeod (1997) categorized risk sources in construction into nine groups, while Ritchie and Brindley (2007) identified seven groups of risk sources in the supply chain although they also mentioned that there are likely myriad other sources of risk that can cause undesirable consequences for a company. A more comprehensive categorization divides risk sources into five groups – production, financial, marketing, human and legal (Crane at al., 2013).

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However, in almost every field of industry a potential risk may be caused by human factor and certain analysis have been performed to determine the impact of human factor on experienced accidents, such as in freight train transportation (Zhang at al., 2019), oil and gas industry (Theophilus at al., 2017), construction industry (Garrett & Teizer, 2009), etc.

This paper deals with the prediction of the change in number of employees in Serbian companies based on information about contingency factors and quality management factors obtained from a questionnaire. The proposed approach is very useful for companies to mitigate risks due to the fact that employee turnover has concealed expenses, such as productivity loss, workplace safety problems, and morale harm, and it affects organizational revenue. After reliability analysis, which served for eliminating unreliable data from a survey, correlation analysis method is used for determination of statistical relationship between survey variables in order to extract factors that have impact on the change in number of employees. In continuation, feedforward neural network (FFNN) is trained to predict level of change in number of employees treating this problem as classification task and finally conclusions are given.

2. LITERATURE REVIEW

Nowadays, in order to meet increasing and more sophisticated expectations and demands of the market, companies improve and modernize production processes, equipment, and internal organization. Organizational design is very useful to mitigate risks (Roberts & Libuser, 1993), while there a human capital is a very important asset (Bukowitz et al., 2004; Seclen-Luna et al., 2020). Clearly, number of employees in companies does have an impact on potential risks. As companies grow larger and stronger, the number of employees also increases, which brings with it a greater capacity, but also the possibility of risk exposure. For example, Becker-Blease at al. (2010) investigated a connection between the size of a firm and its profitability, while Meyer et al. (2011) analyse influence of human resources risk management and its impact on companies' performance indicators. In a huge number of works, the number of employees is considered the most important factor for describing the size of the company (Spasojevic Brkic & Mihajlovic, 2023). As an additional criterion, total income or, in rarer cases, income from sales was most often used (MorenoLuzón & Peris, 1998). Further, companies with more employees require more resources, advanced technologies, adequate structural organization, specific expertise, more sophisticated risk management strategies, etc. On the other hand, a decreasing number of employees may lead to lower quality or productivity because the workload increases for the remaining employees who may be dissatisfied with the greater amount of work (Meyer et al., 2011). It is necessary for companies' management to predict the change in number of employees in future period in order to adjust work environment, spot possible risks and prevent them, adapt their strategy on the market and make the most optimal future plans and decisions. Numerous studies in the existing literature attempt to identify important reasons for employee turnover, investigate the relationship between employees' work motivation and turnover, and job success and turnover, but turnover prediction models are not accessible (Prihandinisari et al., 2020). The application of newer, modern methods in management enables a broader range of understanding of the impact of all relevant factors, leading to improved strategies, more optimal decision making and better leadership. One of the techniques that is progressively being applied in practically all areas of industries, professions and work is artificial intelligence (AI). AI is a discipline that deals with the creation of systems that mimic human intelligence. Subset of AI, that uses all approaches that enable machine to learn from available source of data and algorithms, without especially being programmed for certain task is called machine learning (ML). Finally, deep learning (DL) represents subset of ML that includes all computational algorithms and models that emulate the structure and working way of the biological neural networks known as artificial neural networks (ANN). ANN are often used in the field of human resources. Dutta and Bandyopadhyay (2020) proposed feedforward neural network (FFNN) model for predicting employee attrition which outperformed six other classifiers that were used for comparison with achieved accuracy of 87.01%. Sharma at al. (2022) recognised the problem of increasing work stress level among Indian workers and developed a deep recurrent neural network model for stress detection system for working professionals. In order to predict safe work behaviour in construction project, Patel and Jha (2015) trained FFNN using ten safety climate constructs. Their results showed that absolute percentage deviations for 22 different data samples were in range from 0.03 to 10.15 which is in a permissible range. Some researchers combined various methods and techniques in order to achieve better results and performance of ANN. Anitha and Vanitha (2021) proposed novel technique for prediction of stress for working employees. They used ANN to eliminate unessential attributes from dataset following with the lion optimization algorithm as classifier. This model achieved accuracy of 90.9%. Another method that is often used for prediction and classification problems is by using systems that combine ANN with fuzzy logic and they are called adaptive neuro fuzzy inference systems (ANFIS). Soni at al. (2018) compared ANN and ANFIS for employee turnover prediction in organization, but their research showed that ANN is more optimal solution for that particular problem. ANN combined with analytics hierarchy process (AHP) is also used in risk management which refers to human resources. Yan (2009) investigated employee dismission risk assessment by using mentioned AHP-ANN strategy. Forecasting ratio of demission has ended with absolute value of maximum error 0.0621, while minimum value is 0.0109. Correlation analysis prior to training of ANN was applied by Al-Darraji at al. (2021). Their goal was to extract the most dominant factors for training ANN to predict employee attrition. In three experiments that were conducted, the best achieved accuracy is 94%. They also proved how imbalance in dataset affects ANN performance, as accuracy for imbalanced dataset amounts about 91%.

3. METODOLOGY

This research takes place in two steps. In the first step Spearman's rank correlation coefficient is calculated for determining the strength of relationship between level of change in the number of employees and individual contingency and quality management factors. By using this method, the most crucial factors are identified and taken into consideration in the continuation of research. The second step is training of FFNN model. The input data in model are the main factors selected in the previous step, while the output is degree of change in the number of employees.

3.1. Survey description

The questionnaire used in this study was completed by 67 different companies based in Serbia. Of the total number of companies that participated in the survey, 46.27% are small companies with up to 50 employees, 28,36% are medium companies with a number of employees between 50 and 250, and 25.37% are large companies with more than 250 employees. Also, 10.45% of them are companies established before 1950, 46.27% started in between of 1950 and 2000, and 43,28% are companies founded after 2000. Description of the survey, after reliability analysis, is given in the continuation of the paper.

Group of contingency factors include six subgroups – demographical, environmental, technological, strategical, leadership style and employee behaviour factors, as in Spasojević Brkic (2009). Demographical factors refer to the number of employees, proportion of highly educated employees, percentage of highly qualified employees with long term experience and establishment year of a company. Environmental factors describe the level of heterogeneity (if market and consumer taste vary) and the level of technological sophistication and complexity of the environment, referring to frequency of introducing new and innovating existing products. Technological factors show automatization level, the use of specialized computer programs and technological level compared to competitor companies. Strategical factors refer to the frequency of innovating process and products, monitoring and reducing costs, the level of efficiency in the use of existing technologies, the importance given to planning and detailed elaboration, the analysis of all main factors when solving problems and frequency of having alternative solutions. Leadership style factors describe the level of proactive thinking of managers, dedication to planning alternative solutions, frequency of motivating and rewarding employees. Finally, employee behaviour factors quantify the extent to which quality is a strategic goal of employees, the desirability level of innovations, the level of proactive thinking in order to prevent potential problems, relationship among employees, atmosphere of cooperation and solidarity, the level of non-formal relationships between employees, employee openness to socialization, rarity of confrontation and presence of team spirit.

Quality management factors are divided in four subgroups, as in Brkić et al. (2016). There are factors of leadership and management support to quality program, factors of training and involvement of employees, process approach factors and quality improvement factors. Factors of leadership and management support to quality program include the degree of taking responsibility for quality and supervision of quality system documents usage by sector directors, the level of long-term vision of company's management for quality improvement, the level of understanding and implementation quality policy by every employee and the level of understanding of quality regulations by employees. Factors of training and involvement of employees include the degree of giving importance to the training and development of employees by management, the frequency of providing financial support for training of employees, giving special importance to employee training for application of quality improvement techniques and methods. Process approach factors define the level of process description and delineation, supervision and improvement of key processes and determination of quality measure for each process in the company. Lastly, quality improvement factors describe the frequency of removing internal processes that result in irrational spend of money and time, the degree of use of information technologies for data analysis and revision of quality system documents and the scope of usage of the methods and techniques for quality improvement. Of the 22 quality improvement methods proposed in the survey, later analysis has shown that only 5 are relevant to this research so only these are mentioned in this paper. Those methods/techniques are flow diagram, network plan, internal audit, sampling and acceptance methods and value analysis.

All mentioned factors are described by using five-point Likert scale except for the demographical factors which are individual for every company. In Table 1 are given demographic factors that are part of the contingency factors, but described differently than other factors.

Table 1. Demographic factors

		Factors
Contingency factors	Demographic factors	Q1: Current number of employees
		Q2: Percentage of highly educated employees
		Q3: Percentage of highly qualified employees with long term experience
		Q4: Year of the establishment of the company

Table 2 lists contingency factors described with Likert scale, their reliability values and descriptive statistics.

Table 2. Descriptive statistics and reliability analysis of contingency factors

		Factors	Mean	Std. Deviation	Cronbach's alpha
Contingency factors	Environmental factors	F1: Environment heterogeneity	3.37	1.301	0.635
		F2: Technological sophistication and complexity	3.36	1.422	
	Technology factors	F3: Degree of automatization	3.55	1.019	0.674
		F4: Usage of specialised computer programs	3.96	1.093	
		F5: Technological level compared to competitors	3.64	0.995	
	Strategical factors	F6: Innovating products and processes	3.52	1.330	0.737
		F7: Supervision and reduction of costs	4.09	1.190	
		F8: Efficiency level using existing technologies	4.01	0.977	
		F9: Given importance to detail planning	3.66	1.188	
		F10: Solving problems by analysing all main factors	3.96	1.134	
	Leadership style factors	F11: Proactive thinking of company manager	3.81	1.328	0.836
		F12: Dedication of planning alternative solutions	3.82	1.167	
		F13: Motivating and rewarding employees	3.69	1.131	
	Employee behaviour factors	F14: Quality is strategic goal of employees	4.34	1.122	0.762
		F15: Desirability level of innovations	4.04	1.134	
		F16: Proactive thinking for problem prevention	3.91	1.097	
		F17: Good relationship between employees	3.76	1.292	
		F18: Cooperation and solidarity atmosphere	3.88	1.200	
		F19: Unformal relationship between employees	3.63	0.935	
		F20: Employee openness to socialization	3.84	0.790	
		F21: Rarity of confrontation between employees	3.84	1.009	
		F22: Presence of team spirit	3.57	1.258	

Table 3 shows quality management factors and their reliability values along with descriptive statistics.

In further analysis, these 44 factors presented in Table 1,2 and 3 are observed as independent variables of the model, influencing one dependent variable – which is the change in the number of employees in the observed companies. The level of change in the number of employees was also quantified but due to the large range of the data, it was logarithmized for the purpose of data normalization and harmonizing the scale with other factors to fit the Likert scale.

3.2. Correlation analysis

In this research Spearman's rank correlation coefficient is calculated in order to determine the strength of relationship between 44 factors, presented in Table 1, 2, and 3 and the level of change in the number of employees. It is the nonparametric rank statistic which measures degree of association between two variables (Hauke and Kossowski, 2011). Spearman's rank corelation coefficient, marked with ρ, can take a value between -1 and 1 and it is calculated using following expression:

$$\rho = 1 - \frac{6\sum di^2}{n(n^2-1)}, \tag{1}$$

Where d_i represents the distance between the ranks of corresponding variables, and n is number of observations. If ρ is equal to zero, it means that there is no relationship between variables, while values 1 and -1 denotes perfect and perfect negative relationship of variables, respectively.

Table 3. Descriptive statistics and reliability analysis of quality management factors

		Factors	Mean	Std. Deviation	Cron. alpha
Quality management factors	Leadership and management support to quality program	F23: Taking responsibility for quality and supervision of usage of quality system documents	4.19	1.004	0.777
		F24: Level of long-term vision for quality improvement	4.16	0.963	
		F25: Company goals and quality policy are understood and implemented by all employees	4.13	1.013	
		F26: Quality regulations are understood by employees	3.88	1.080	
	Training and involvement of employees	F27: Importance attached to training and development of employees by company management	4.06	1.127	0.804
		F28: Frequency of providing financial support for training of employees by company management	3.76	1.195	
		F29: Giving importance to the training of employees for the usage of quality improvement methods	3.63	1.229	
	Process approach factors	F30: Companies processes are precisely described and delimited	3.67	1.307	0.883
		F31: Constantly monitoring and improving key processes	3.94	1.217	
		F32: Determination of quality measure for every process preformation	3.84	1.136	
	Quality improvement factors	F33: Removing internal processes that result in unreasonable spending of money and time	2.88	0.844	0.736
		F34: Usage of advanced information technologies for data analysis	3.61	1.267	
		F35: Revision of quality system documents as necessary	3.54	1.172	
		F36: Range of usage of flow diagram as quality improvement technique	3.69	1.183	
		F37: Range of usage of network plan as quality improvement technique			
		F38: Range of usage of internal audit as quality improvement technique			
		F39: Range of usage of sampling and acceptance methods for quality improvement			
		F40: Range of usage of value analysis as quality improvement technique			

3.3. Feedforward Neural Networks

FFNN represents type of ANN whose architecture is organized into input, hidden and output layers. There can be one or more hidden layers in network model. They are often used for solving regression, clustering, prediction or classification problems.

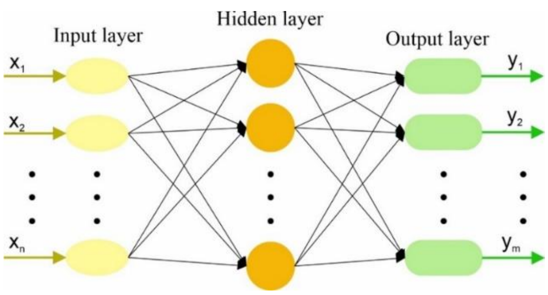

Figure 1. Structure of feedforward neural network

Figure 1. shows structure of FFNN with one hidden layer. In this study, developed FFNN has 18 input data, 6 neurons in hidden layer and 5 neurons in output layer.

Training of neural networks implies adjustment of weight coefficients and biases of neurons. The back propagation (BP) algorithm is one of the most commonly used learning algorithms. It minimizes adopted cost function by recursively adjusting weight coefficient and biases based on gradient descent techniques (Leung and Haykin, 1991). Standard BP algorithm often causes slow convergence to a solution, so faster algorithms based on BP are used. In this research, scaled conjugate gradient BP algorithm (Moller, 1993) is applied. Cost function measures error between predicted output by ANN and desired output. Cross-entropy is used as cost function and it can be presented via:

$$Loss = -\sum_{i=1}^{m} y_i \cdot \log \hat{y}_i, \tag{2}$$

where y_i is desired output, $\hat{y}_i$ is predicted output and m is size of outputs. Activation function of neurons in hidden layer is hyperbolic tangent function, while neurons in output layer use softmax activation function.

4. RESULTS AND DISCUSSION

This section includes results of correlation analysis, which served for neural network training and the results obtained by FFNN.

4.1. Correlation analysis

Figure 2 shows absolute values of Spearman's rank correlation coefficients between every factor Q1-Q4 and F1-F40 and yearly change in the number of employees, which is described via Likert scale where 1 represents decrease and 5 represents increase in number of employees.

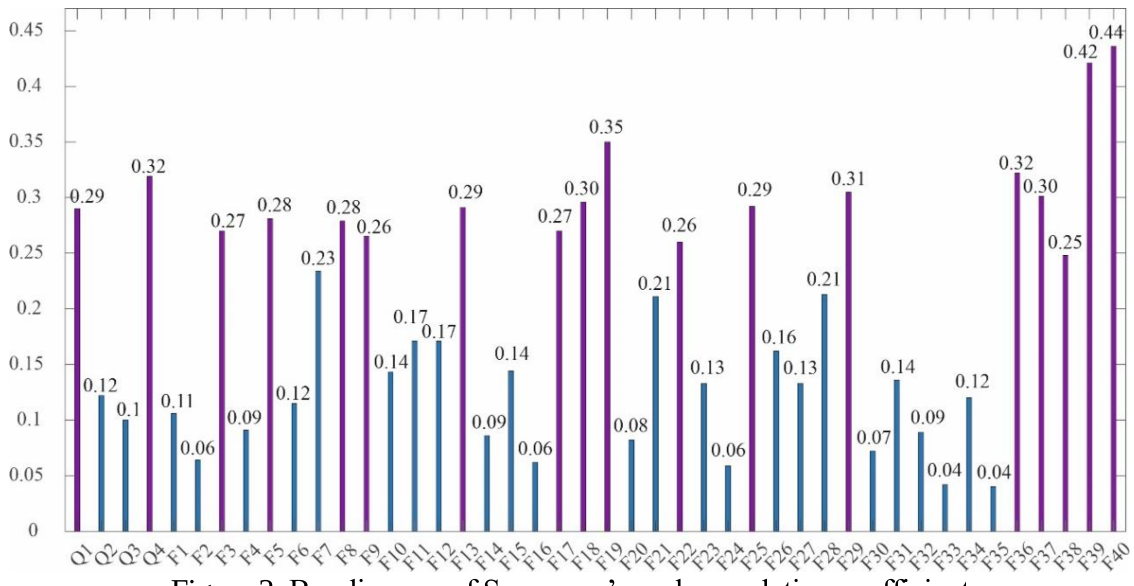

Figure 2. Bar diagram of Spearman's rank correlation coefficient

It is considered that all factors whose coefficient is equal or greater than 0.25 are in correlation with subject of interest. From figure 2 it is clear that main factors are Q1, Q4, F3, F5, F8, F9, F13, F17, F18, F19, F22, F25, F29, F36, F37, F38, F39 and F40, so they are taken in consideration in the second phase of research.

4.2. Feedforward Neural Networks

Inputs in FFNN are 18 selected main factors, while output determines class that our sample belongs to. There are 5 classes, one for every Likert scale value, which explains number of neurons in output layer. From the total of 67 different samples, 80% are used for training, 10% are used for validation and 10% are used for testing our model. The distribution of data in every set is random. In order to prevent overfitting, training of model is interrupted when value of cross-entropy cost function starts to increase in validation process. The minimum value of cross-entropy loss is about 0.22 at 13th epoch. Figure 3 shows the changes in the values of the cost function for train, validation and test set of data during epochs.

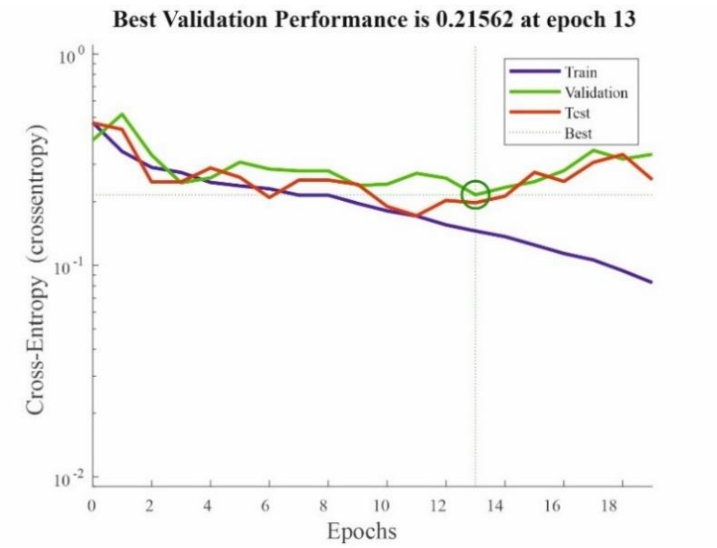

Figure 3. Cross-Entropy loss function

Overall accuracy, precision and recall are calculated as a measure of performance of proposed FFNN model. They are presented in table 4.

Table 4. Accuracy, precision and recall

	Training	Test
Overall accuracy	77.36%	71.43%
Overall precision	73.3%	75%
Overall recall	59.58%	72.23%

5. CONCLUSION

This study deals with the problem of prediction of the change in number of employees in Serbian companies, as it one of the company development factors. Number of employees is important both from human resources management and risk management fields, and according to this survey it could be based on contingency and quality management factors. FFNN model is offered as a solution for this task. In order to achieve the best possible prediction results, survey data are analysed and Spearman's rank correlation coefficients are calculated, resulting with selection of 18 main factors for training of FFNN. Proposed model, which contains degree of automatization, technological level compared to competitors, efficiency level of using existing technologies, given importance to detail planning, motivating and rewarding employees, good relationship between employees, cooperation and solidarity atmosphere, unformal relationship between employees, presence of team spirit, company goals and quality policy which are understood and implemented by all employees, giving importance to the training of employees for the usage of quality improvement methods, range of usage of flow diagram as quality improvement technique, range of usage of network plan as quality improvement technique, range of usage of internal audit as quality improvement technique, range of usage of sampling and acceptance methods for quality improvement, and range of usage of value analysis as quality improvement technique, achieved accuracy of 77.36% in training and 71.43% in testing. Accordingly, it is recommended to companies to pay special attention in the future to those factors and to use the proposed model. The benefits of this model are in ease of use and implementation and learning is very fast. However, the accuracy of neural network can still be considerably improved. The proposal for the further research is implementing ANN model with different structure, trying other learning algorithm or combining FFNN with other analysing techniques. Also, by expanding of dataset, there would be more samples for learning of neural network, which can positively affect the accuracy.

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