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FORECASTING ELECTICITY IN PHOTOVOLTAIC POWER PLANTS

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Abstract: Due to the increasing global demand for sustainable energy and the variable nature of solar radiation, accurate forecasting of photovoltaic (PV) system performance has become essential. This study focuses on the development of an artificial neural network (ANN) model to predict monthly electricity production in a rooftop photovoltaic power plant. The model uses meteorological inputs such as direct normal irradiation, diffuse radiation, and average monthly temperature, covering the period from January 2017 to December 2023. The ANN demonstrated high predictive accuracy and reliability, making it a valuable tool for energy management, planning, and integration of PV systems into power grids. While the dataset spans 2017–2023, the model is structured to allow generalization for future forecasting applications under similar input conditions.

Keywords: photovoltaic power plants, electricity forecasting, artificial neural networks, renewable energy

INTRODUCTION

The adaptation of the primary energy resource to the consumption plays a key role in energy management policies. In this context, renewable energy sources have a significant importance. However, due to their variable nature, predicting their availability is a significant challenge.

Special attention is paid to predicting the amount of electricity that can be obtained through solar radiation on photovoltaic panels. This prediction depends on various external factors, including air temperature, cloudiness and humidity. Previous research has shown that methods such as machine learning and artificial neural networks are very effective in predicting and optimizing the operation of solar energy systems. Therefore, accurate forecasting of the power output of PV systems is critical to the proper planning and operation of power system [1].

Artificial neural networks (ANN) have been recognized as a powerful tool for solving complex problems, as they can process incomplete data and enable fast predictions. An ANN can be viewed as a black box model in which input factors pass through the neural network system, giving the corresponding output results.

One of the most commonly used types of neural networks is a multilayer network with a back-propagation error algorithm, which allows for a complex mapping of the relationship between input and output data. In this research, this very algorithm is used to create a prediction model for energy production from photovoltaic systems, with the aim of more accurately predicting their output power.

The remainder of this paper is structured as follows: Section 1 provides a background on artificial neural networks and their relevance to photovoltaic forecasting. Section 2 describes the case study of the "Mazoljice" solar power plant and the solar energy potential in Mostar. Section 3 outlines the dataset and the model-building process. Section 4 presents and discusses the results, while Section 5 concludes with final remarks and potential applications.

1. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are computational models inspired by the structure and functionality of the human brain, designed to recognize patterns and relationships in data through interconnected layers of neurons. Due to their ability to approximate complex nonlinear relationships, ANNs have become increasingly prominent in forecasting applications, particularly in the renewable energy sector.

In the context of photovoltaic (PV) systems, where electricity generation is strongly influenced by fluctuating environmental parameters such as solar irradiance, temperature, wind, and cloud cover, conventional linear models often fail to capture the underlying dynamics. ANNs, on the other hand, are capable of learning from historical data and adapting to complex conditions, making them highly effective for modeling solar energy production.

Numerous studies have demonstrated the superior performance of ANN-based models over traditional methods. For instance, Izgi et al. [2] applied artificial neural

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networks for short- and mid-term solar power prediction and showed that they significantly outperformed statistical approaches such as ARIMA, particularly under volatile weather conditions. Similarly, Khatib et al. [5] developed a multilayer perceptron (MLP) ANN model in Malaysia using four input variables—temperature, humidity, solar radiation, and sunshine duration—achieving excellent predictive performance in a tropical climate.

A more advanced approach was presented by Ramsami and Oree [1], who proposed a hybrid model that combines ANN with time-series decomposition. By separating solar irradiance data into trend and seasonal components, and using ANN to predict each independently, the authors managed to improve the overall forecast accuracy and reduce generalization error. This hybrid technique is particularly useful in regions with pronounced seasonal solar variation, such as Southeast Europe.

In addition to their predictive capabilities, ANNs have proven versatile across various renewable domains. Cobaner et al. [3] successfully applied ANN models for hydropower energy prediction, confirming the general adaptability of neural networks to energy systems with environmental dependencies. While not directly related to solar energy, the study provided a methodological foundation relevant to PV system modeling, particularly in how input variable selection and training data quality impact prediction accuracy.

Further development of ANN models for PV forecasting was provided by Saberian et al. [4], who implemented a feedforward ANN using input parameters such as irradiance, temperature, and panel voltage. Their study emphasized the importance of sensitivity analysis to identify key predictors and simplify the model architecture without compromising accuracy. This is especially relevant for rooftop PV systems, where input data may be limited or noisy due to localized conditions and varying installation geometries.

Abuella and Chowdhury [6] highlighted the operational benefits of ANN-based forecasting in real-time grid management scenarios. Their study demonstrated how ANNs can be integrated with supervisory control systems to aid short-term energy dispatch decisions. Such applications are critical for rooftop systems in decentralized networks, where variability in production can challenge grid stability.

In terms of network design, determining the appropriate number of neurons in the hidden layer remains an important consideration. Karsoliya [7] proposed practical formulas to estimate this number based on the size of the input and output layers and the training dataset. These heuristics help balance model complexity and performance, and were utilized in the present study during the design and optimization of the ANN topology.

Kalogirou and Bojic [8] stressed the importance of incorporating site-specific variables into ANN models, particularly in small-scale and passive solar systems. Their findings support the adaptation of ANN structures to localized rooftop PV installations, where factors such as shading, roof angle, and microclimate play a significant role in system performance. Despite being originally focused on energy consumption, their methodology and conclusions remain applicable to PV output forecasting.

Anang, Syd Nur Azman and Muda [9] present a comprehensive analysis of the performance of a 7.8 kWp grid-connected rooftop photovoltaic (PV) system installed on a residential house in Malaysia under the feed-in tariff (FiT) scheme. Unlike PV systems installed on flat roofs or open land, rooftop installations are constrained by the existing roof tilt and orientation, which directly impact energy efficiency. Using PVsyst software, it was found that a 5° tilt and proper orientation can increase annual energy production by up to 4.8%. By calculating the system's derating factor and incorporating it into simulations using HOMER Pro, a high level of accuracy was achieved compared to actual measurements (with only 1.7% annual error). The economic analysis indicates that such rooftop systems can generate significant annual profit and offer a short payback period of 5–7 years, while also contributing to CO_2 emissions reduction. These results confirm that well-designed rooftop PV installations represent a sustainable and practical solution for the residential sector, with strong potential for wider adoption.

In summary, the literature supports the use of artificial neural networks as a reliable and adaptable tool for forecasting photovoltaic system performance. While many studies focus on large-scale installations, there remains a notable gap in addressing the specific characteristics and forecasting needs of rooftop PV systems. This paper contributes to closing that gap by applying an ANN model to a real-world rooftop installation in Mostar, Bosnia and Herzegovina, using climate data and system performance measurements to demonstrate the feasibility and accuracy of this approach.

2. CASE STUDY OF THE "MAZOLJICE" SOLAR POWER PLANT AND SOLAR ENERGY POTENCIAL IN MOSTAR

Mostar, located in Bosnia and Herzegovina, has a significant solar energy potential due to its favorable climate and geographic position. The city enjoys a high number of sunny days throughout the year, with an average solar irradiance ranging between 4.5 to 5.0 kWh/m² per day. This makes Mostar an excellent candidate for solar energy projects, both for residential and commercial use.

The abundant sunlight can be harnessed through photovoltaic (PV) panels or solar thermal systems to generate electricity and heat, contributing to sustainable energy production and reducing dependence on fossil fuels. Given the growing interest in renewable energy in the region, Mostar has the potential to become a key player in solar energy development, helping to support environmental goals and economic growth.

Furthermore, the integration of advanced forecasting models, such as artificial neural networks (ANNs), can enhance the efficiency and reliability of solar energy systems in this region. Accurate short-term and long-term prediction of solar power generation is essential for effective grid management, energy storage optimization, and investment planning. The combination of high solar potential and intelligent data-driven systems presents an opportunity to develop decentralized energy networks, improve energy security, and create new jobs in the renewable energy sector.

In addition, educational and research institutions in Mostar can play a vital role in supporting innovation through the development and testing of smart energy technologies.

With appropriate governmental incentives, international collaboration, and investment in infrastructure, the city could establish itself as a regional hub for solar energy research, deployment, and training, setting an example for other cities in Southeast Europe.

The solar power plant SE “Mazoljice” represents a modern and efficient example of the use of renewable energy sources. The system is designed as a rooftop installation on a single building, demonstrating how solar technology can be effectively applied in smaller, individual systems.

The plant utilizes solar energy as its primary source and is designed to generate approximately 10.08 MWh of electricity annually. A total of 40 photovoltaic panels have been installed, covering an area of 65.07 m². The installed capacity of the system is 10 kWp (DC) and 10 kW (AC), providing stable performance to meet the expected annual output.

Additional technical data confirm the plant’s efficiency. The expected number of operating hours per year is 4,379, and the system achieves an overall system efficiency of 10.60%. Furthermore, it contributes significantly to environmental protection by reducing CO_2 emissions by 8,963 kg annually. The yearly yield per installed kilowatt of capacity is 1,008 kWh/kWp, which is a strong result for this type of installation.

The photovoltaic panels used in the system are manufactured by Risen, model SYP250. Each panel has dimensions of 1,640 × 992 × 40 mm and consists of 44 solar cells (2 strings of 22 cells). The weight of a single panel is 19.5 kg, with a nominal power output of 250 Wp. The rated current of the panel is 8.23 A, and the rated voltage is 30.48 V, which contributes to reliable and efficient energy generation.

To convert the DC power from the panels into AC power suitable for the grid, the system uses a Kaco inverter, model Powador 12.0 TL3. This inverter has a maximum DC power input of 10.20 kW and can handle up to 950 V of input voltage. Its nominal AC output is 10.00 kW, with a voltage of 230/400 V and a maximum output current of 14.5 A. The inverter achieves a high efficiency rating of 98.0%, indicating minimal energy loss during the conversion process.

The plant is managed automatically using the Kaco Powador proLOG system, with a grid connection power of 12 kVA. These specifications demonstrate the system’s reliability, stability, and compliance with modern technical standards.

All of this shows that SE “Mazoljice” is not only energy-efficient but also an environmentally responsible investment, contributing to the development of sustainable energy and reducing the negative impact on the environment.

Table I shows the technical specifications of the ‘Mazoljice’ solar power plant.

Table I: Technical specifications of the power plant

Solar Power Plant	Technical specifications
Name	SPP “Mazoljice”
Location	Mostar, BiH
Total annual radiation for the location	1690 kWh/m²
Type of installation	Roof-mounted
Number of buildings on which solar panels are installed	1
Total surface area where solar panels are installed	65,10 m²
Total number of photovoltaic panels in SPP	40
Total installed capacity of the SPP (DC side)	10 kWp
Total installed capacity of the SPP (AC side)	10 kW
Number and unit of measurement for monitoring	1x10,00 kW
Projected annual electricity production of the SPP	10,08 MWh
Expected operational lifetime of the SPP	4379 h
CO2 emission reduced (calculated using PVSOL 4.5)	8963 kg/year
Overall nominal efficiency	10,60 %
Energy yield per 1kW of installed capacity	1008 kWh/year
Monitoring and control system	Kaco Powador proLOG
Control mode	automatic
Connection point	-

Table II shows the technical-energy characteristics of equipment used in “Mazoljice” solar power plant.

Table II. Technical-energy characteristics of equipment

Technical-energy characteristics of equipment	
Photovoltaic panels	
PV panel manufacturer	Risen
PV panel type	SYP250
Length/width/thickness	1640x992x40 mm
Number of PV cells in panel	2x22
Weight of PV panel	19,5 kg
Power rating of PV panel	250 Wp
Nominal current of PV panel	8,23 A
Nominal voltage of PV panel	30,48 V
Inverter	
Inverter manufacturer	Kaco
Inverter type	Powador 12.0 TL3
Maximum DC power of the inverter ($\cos\zeta = 0$)	10,20 kW
Maximum DC voltage of the inverter	950 V
Rated AC power of the inverter	10,0 kW
Rated AC voltage of the inverter	230/400 V
Maximum output current of the inverter	14,5 A
Maximum efficiency of the inverter	98,0 %

3. THE MODEL BUILDING

In order to conduct a comprehensive study of the relationship between photovoltaic forecast and climate, the prediction model is relying on data from monthly global horizontal irradiation, direct normal irradiation and monthly average temperature from the January 2017 to December 2023. The dataset used for training, validation, and testing of the ANN model consists of 84 monthly samples. These were divided into training (70%), validation (15%), and testing (15%) subsets using random stratified sampling, ensuring balanced representation across seasons and years. Input parameters include global horizontal irradiation, direct normal irradiation, and monthly average temperature, while the target output is the monthly energy production of the photovoltaic system. This data is provided by PVGIS software.

Table III shows the technical characteristics of the “Mazoljice” solar power plant. The table presents maximum, minimum, and average values for temperature, global horizontal irradiation, direct normal irradiation, and the amount of energy generated. The highest recorded temperature is 22.70°C, while the lowest is -5.90°C. Global horizontal irradiation ranges from 34.60 to 233.88 kWh/m², and direct normal irradiation varies between 42.09 and 250.82 kWh/m². The generated energy reaches a maximum of 1606 kWh and a minimum of 206.46 kWh, with an average value of 907.28 kWh. These data provide insight into the plant’s performance under different environmental conditions.

Table III: Maximum, minimum and average values of data used for ANNs model

	Temp. [°C]	Global horizontal irradiation	Direct normal irradiation	Generated energy [kWh]
Max	22.70	233.88	250.82	1606
Min	-5.90	34.60	42.09	206.46
Average	10.35	126.28	137.68	907.28

The neural network adopted was a feed forward multilayer perceptron network. A schematic flowchart diagram for building model is shown in Figure 1 and block diagram of the ANNs topology is shown in Figure 2.

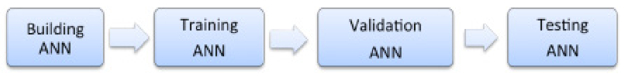

Figure 1: Flowchart diagram for building an ANNs model

Pre-processing of the data is usually required before presenting the data to the network model when the neurons have a transfer function with bounded range. In this study the data were scaled to range between 0 and 1.

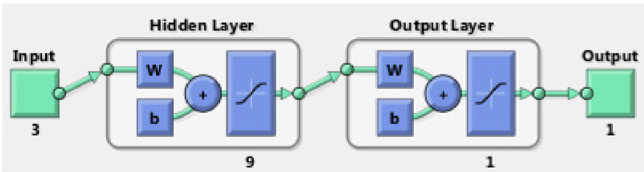

Figure 2: Block diagram of the ANNs topology

The number of neurons in the hidden layer is determined by various factors, including the number of input and output variables, the complexity of the activation function, the architecture of the neural network, and most importantly, the dataset used to train the artificial neural network. Guidelines for determining the number of neurons in hidden layers can be determined as follows:

1) Number of neurons in hidden layer should be 2/3 (70% - 90%) input neurons. In some cases number of neurons in output layer can be added [6]
2) Number of neurons in hidden layer shouldn’t be greater than twice of number of neurons in input layer [7]
3) Number of neurons in hidden layer should be 1/2 (input neurons + output neurons) + number of training data1/2 [8]

In this paper the optimum neurons number in the hidden layer was determined using trial and error procedure by varying the hidden neuron number from 2 to 10. The best performing network was chosen based on variation of the number of neurons in hidden layer while monitoring the performance criteria, table IV.

Table IV: Results of trained ANNs models

Num. of neurons	Iteration/ Epoch	Performance	Regression
2	148	0.0007564	0.95793
3	34	0.00065905	0.9981
4	11	0.00086474	0.99776
5	14	0.00033011	0.99798
6	38	0.0002396	0.99824
7	6	0.00040646	0.99801
8	11	0.00030052	0.99685
9	**42**	**0.00047214**	**0.99826**
10	14	0.00042687	0.99811

The results indicate that increasing the number of neurons generally improves prediction accuracy and regression performance up to a certain point. However, there's a trade-off with training time, and overcomplicating the model (with too many neurons) might lead to diminishing returns.

The models with 5, 6, and 9 neurons appear to offer the best balance between accuracy and efficiency. The bolded values indicate the number of neurons yielding the highest regression accuracy.

4. RESULTS AND DISCUSION

Figure 3. shows a comparison between the measured and predicted monthly energy production of the chosen site. Based on the results the best ANN topology was neural network with one hidden layer and nine neurons in hidden layer.

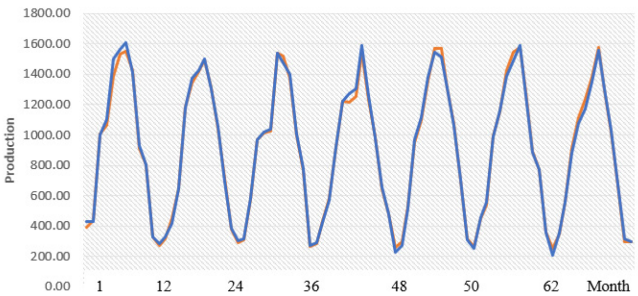

Figure 3: Comparison between measured and estimated values

The graph shows clear seasonal variations in production, with consistent peaks and drops repeating approximately every 12 months. This indicates that production is strongly influenced by seasonal or cyclical factors. The regularity of the pattern suggests that the system is stable over time and predictable.

The comparison between the actual and predicted values (represented by the blue and orange lines, respectively) shows that the model used for forecasting performs very well. The predicted values closely follow the actual data, with only minor deviations at some peak points. This confirms that the model effectively captures both the trend and seasonality of the production process.

Overall, the results suggest that the production system is reliable and that the forecasting model can be confidently used for future planning and decision-making.

Figure 4. presents the results from the ANN model for different stages, including training, validation, test and together.

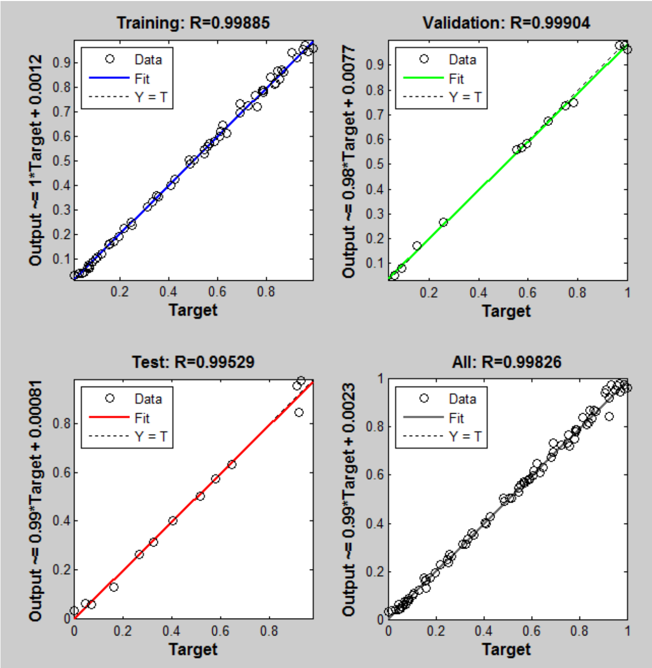

Figure 4: ANN results under the multi-layer training algorithm: for training, for validation, for test and for all

The regression plots demonstrate that the developed model exhibits excellent predictive performance. The correlation coefficients (R-values) for all data subsets—training (R = 0.99885), validation (R = 0.99904), and testing (R = 0.99629)—are very close to 1, indicating a very strong linear relationship between the predicted outputs and the actual target values. This suggests that the model has successfully learned the underlying patterns in the data without overfitting.

The minimal deviation of the data points from the ideal line (Y = T) in all four plots confirms that the model's predictions are highly accurate. The performance on the validation and test sets being nearly as good as on the training set shows that the model generalizes well to new, unseen data.

Overall, the high R-value for all data combined (R = 0.99826) further supports the conclusion that the model provides reliable and consistent predictions. These results validate the effectiveness of the model for practical application in predicting the target variable based on the input data. Results show that ANNs are able to predict the power output of a PV panel.

5. CONCLUSION

The primary objective of this study was to predict monthly power generation in a solar power plant using artificial neural networks (ANNs), considering the impact of climate variability. To achieve this, a feed-forward neural network with a single hidden layer was developed and trained.

As input variables, key climatic parameters were selected: global horizontal irradiation, direct normal irradiation, and monthly average temperature. These inputs were chosen due to their direct influence on photovoltaic energy generation. The output of the model was the monthly energy production of the solar power plant. Historical data for both inputs and output were collected for the period from 2017 to 2023, ensuring a robust dataset with seasonal and interannual variability.

The developed ANN model demonstrated excellent predictive performance, achieving a high correlation coefficient (R = 0.99826) between the predicted and actual values. This indicates a very strong agreement and minimal prediction error. The results confirm that the model successfully captured the nonlinear relationships between climatic conditions and energy output, making it a reliable tool for forecasting future solar power generation.

Furthermore, the high accuracy of the model implies its potential application in energy management, planning, and optimization of solar power plants. It can be particularly useful for anticipating energy production under varying climate conditions, supporting the integration of renewable sources into the energy grid more efficiently.

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REFERENCES

[1] P. Ramsami, V. Oree, A hybrid method for forecasting the energy output of photovoltaic systems, Energy Conversion and Management 95. (2015). Accessed: March 16, 2025. [Online]. Available:https://www.researchgate.net/publication/276452312_A_hybrid_method_for_forecasting_the_energy_output_of_photovoltaic_systems

[2] E. Izgi et al, Short–mid-term solar power prediction by using artificial neural networks, Solar Energy 86. (2011). Accessed: March 16, 2025. [Online]. Available:https://doi.org/10.1016/j.solener.2011.11.013.

[3] M. Cobaner et al, Prediction of Hydropower Energy Using ANN for the Feasibility of Hydropower Plant Installation to an Existing Irrigation Dam, Water Resour Manage 22. (2008). Accessed: March 16, 2025 [Online]. Available: https://doi.org/10.1007/s11269-007-9190-z

[4] A. Saberian at al, Modelling and Prediction of Photovoltaic Power Output Using Artificial Neural Networks. International Journal of Photoenergy. (2014). Accessed: March 16, 2025. [Online]. Available: https://scihub.se/https://onlinelibrary.wiley.com/doi/full/10.1155/2014/469701

[5] T. Khatib at al, Solar energy prediction for Malaysia using artificial neural networks, International Journal of Photoenergy. (2012). Accessed: March 16, 2025. [Online].Available: https://onlinelibrary.wiley.com/doi/full/10.1155/2012/419504

[6] M. Abuella, B.Chowdhury, “Solar power forecasting using artificial neural networks”. North American Power Symposium (NAPS). (2015).
Accessed: March 16, 2025. [Online]. Available: https://www.researchgate.net/publication/282650839_Solar_Power_Forecasting_Using_Artificial_Neural_Networks

[7] S. Karsoliya, “Approximating Number of Hidden layer neurons in Multiple Hidden Layer BPNN Architecture”. International Journal of Engineering Trends and Technology 3. (2012).
Accessed: March 16, 2025. [Online]. Available: https://ijettjournal.org/archive/ijett-v3i6p206

[8] S.A. Kalogirou, M. Bojic, “Artificial neural networks for the prediction of the energy consumption of a passive solar building”. Energy 25(5). (2000). Accessed: March 16, 2025. [Online]. Available: https://www.researchgate.net/publication/222899234_Artificial_Neural_Networks_for_the_Prediction_of_the_Energy_Consumption_of_a_Passive_Solar_Building

[9] N. Anang, S.N.A. Syd Nur Azman, W.M.W. Muda, “Performance analysis of a grid-connected rooftop solar PV system in Kuala Terengganu, Malaysia”. Energy and Buildings (2021). Accessed: Jul 17, 2025. Available:https://www.sciencedirect.com/science/article/abs/pii/S0378778821004667

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BIOGRAPHY

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Obrad Spaić was born in 1959 in Trebinje and graduated from the Faculty of Mechanical Engineering in Mostar in 1983 with excellent grades. He completed postgraduate studies in Management, Informatics, and Quality, defending his master's thesis in 2006 and his doctoral dissertation in 2009 at the Faculty of Production and Management in Trebinje. From 1983 to 2007, he worked in various engineering and management roles at the Trebinje Tool Industry. Since 2007, he has been a full-time faculty member at the University of East Sarajevo, serving as Vice Dean (2009–2021) and Dean (since 2021) at the Faculty of Production and Management.

Dragi Tiro was born in 1968. Graduated from the Faculty of Mechanical Engineering in 1992. Served as assistant (1995–2000), senior assistant (2000–2005), and assistant professor (2005–2010) at the University "Džemal Bijedić" Mostar. Earned a master's degree in 2000 and a doctorate in 2004 from the Faculty of Mechanical Engineering in Zenica. Associate professor (2010–2015) and full professor since 2015 at the same university. Research interests include the application of information technologies in industry, technological processes, mechanical engineering, and higher education.