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Review Paper

Artificial Neural Networks Models in Solar Photovoltaic and Hydropower Forecasting – a Rreview

Modeli vještačkih neuronskih mreža za predviđanja u hidroenergetskim i fotonaponskim solarnim sistemima - pregled

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Abstract: *Many studies have focused on using artificial intelligence in energy systems. The aim of this review paper is providing the insides in methods based on Artificial intelligence used for building models in energy forecasting. This paper also provides a compregensive review of the advantages and disadvantages of available methods as well as the input parmeters used for modelling these models. This paper concentrate on using Artificial Neural Networks (ANNs) in forecasting energy production in renewable energy sources, especially in hydropwer and photovoltaic sistems. The archicetures of ANN-s have also been briefly discussed, such as Multilayer perceptron neural network. Also, some statistical criteria that have been used to assess the performance of ANN modelling have been introduced.*

Keywords: *Artificial Neural Networks, Energy Forecasting, Hydropower, Photovoltaic power plant.*

Apstrakt: *Veliki broj istraživanja je fokusirano na korištenje vještačke inteligencije u energetskim sistemima. U ovom preglednom radu je dat izvod iz istraživanja koja su fokusirana na formiranje modela za predviđanje u energetskim sistemima zasnovanih na vještačkoj inteligenciji. U radu je dat kratak pregled prednosti i nedostataka predloženih modela kao i podataka koji su korišteni za formiranje istih. Rad je fokusiran na vještačke neuronske mreže i na predviđanje proizvodnje iz obnovljivih izvora energije, hidroenergiji i fotonaponskim solarnim sistemima. U radu je dat i kratak opis arhitektre vještačkih neuronskih mreža i neurona. Takođe dat je pregled kriterijuma koji se uglavnom koriste za vrednovanje kvaliteta formiranih modela.*

Ključne riječi: *Vještačke neuronske mreže, planiranje energije, Hidroenergija, Fotonaponski solarni sistemi*

1 INTRODUCTION

Energy as essential factor for economic and social development is one of the key elements of the development of modern society. On the other hand environmental problems that we face today requies actions for sustainable development [1].

All these, the increase in energy consumption, on the one hand and the goals of sustainable development on the other, require periodic review of the existing energy systems, at global and national level, in order to create strategies and plans that will meet the increased energy consumption as well as challenges related to sustainable development.

The political, social, economic and environmental importance of energy planning aims to meet the increasing demand for an adequate source of energy, so the choice of appropriate energy projects, and development of different energy systems become a great challenge for policy makers.

Overcoming concerns about the unpredictibility of renewable energy such as solar and hydro energy is one of the most challenging issues in forecasting energy production. The character of these energy resources such as variations and stochastic power production and the fact that there are viable alternative in the

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generation mix of modern utility grids, smart grids, and microgrids [2] require different forecasting models. These models are crucial as renewable energy sources are integrated in energy systems [3]. Also as the penetration of renewable energy in electrical grid increases accurate forecasting [3] become more and more important for improving economis efficiency [4], so energy forecasting will play an important role for the policy makers to identify the sudden change in demand of electricity under given conditions [5].

Over the last ten years Artificial Intelligene (AI) has become a popular field and many sciences had made researches in domen of AI, Machine Learning (ML) and Artificial Neural Netwoks (ANNs).

AI and ANNs are developing and improving every day, so it is very important to review up to date ways of applying these tools in different fields.

The aim of this paper is to provide an systematic literature review of ANN models used for sustainable energy planning with focus on hydropower and photovoltaic energy systems, since these are the most common type of renewable energy resorces in Bosnia and Hercegovina. Paper is focusing on indentifuing most important input and outpot variables as well as a ANNs approach used for forecasting. The outputs of this review are intended to provide a guide to researchers and other stakeholders for sustainable energy forecasting in hydropower plant and photovoltaic energy systems.

Many papers researched the methods of applying AI and ML techniques that have been used to model energy forecasting in the field of hydropower and solar energy systems [6, 7, 8, 9, 10]. The contribution of this paper lies in a research of the state of the art of ANNs applications in hydropower and photovoltaic energy systems.

2. BACKGROUND

2.1 Artificial Intelligence, Machine Learning and Artificial Neural Network

AI has become a popular subject in the science community and many papers covered the topics of ML, Deep Learning (DL) and AI. AI include classical programming and ML. ML is a field that focuses one the learning aspect by developing algoritmhms that best present a set of data. It contains many models and methods, including DL and ANNs, *Figure 1* [11].

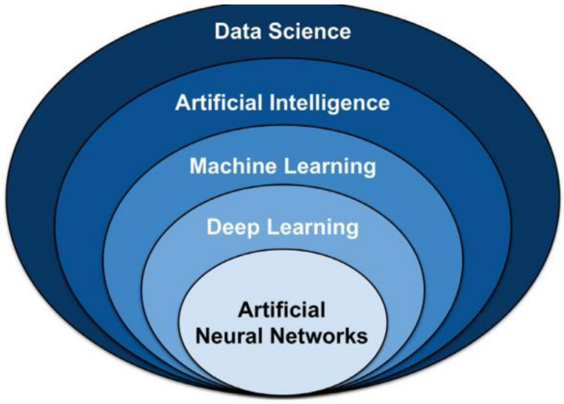

Figure 1 - Umbrella of selecet data science techniques [11]

2.2 Artificial Neural Networks

ANN is a ML algorithm inspired by the human brain. It is made by layers of neurons connected through weighted links. The neuron model (*Figure 2*) consists of a group of connecting links called synapses each of them has weight w_{ij}. This weight is multiplied by its own input x_j before summing all weighed inputs as well as the externally bias b_k which is responsible for increasing the summation output [12]. Activation function is used to decrease the amplitude range of the output into a finite value [12].

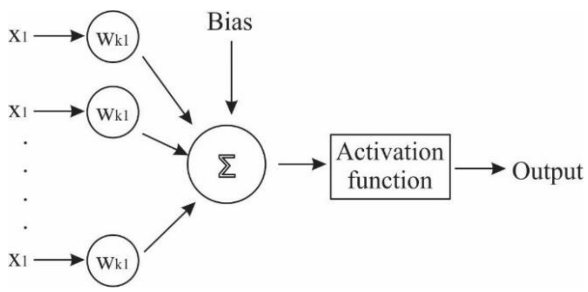

Figure 2 - Sketch of the artificial neuron

Building an ANN-s involves designing their architectures (i.e., number of hidden layers and number of neurons in each layer) and its operating dynamics (i.e., activation function, training algorithms and optimizer) [13]. By training ANNs we adjust the weights to approximate the function that relates inputs and outputs.

For evaluation of quality of ANNs there are set of criteria such as: mean square error (MSE), root mean square error (RMSE), R^2 ... *Table 1.* present definition of some evaluation criteria.

Table 1. Definition of evaluation criteria

Criteria	Equation
Mean square error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n} (A_i - F_i)^2$
Root mean square error (RMSE)	$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(A_i - F_i)^2}{n}}$
R^2	$R^2 = \frac{\sum_{i=1}^{n} (A_i - F_i)^2}{\sum_{i=1}^{n} (A_i - \widehat{A}_i)^2}$

where is:

- n the number of used data,
- A_i actual value of the data,
- F_i is the ANN's forecast value and
- $\widehat{A}_i$ is the average of validation data

The most important feature of ANNs are ability to model nonlinear structures, learning and geranalizaion ability, adaptability and fault tolerance for different problems [14] and it doesn`t require any konwledge between input and output variables.

3 ANNs MODELLING IN ENERGY FORECASTING

The primay objective of the forecasting in energy system is to improve the quality of energy consumption/production in an optimal way. This depends on many parameters like population, energy demand, energy losses in energy grid. Different techniques and mathematical modelling tools have been used in field of forecasting energy. Among all techniques intelligent systems ANNs present useful tool in modeling and simulation in these projects.

3.1 ANNs in hydropower plant forecasting projects

Hydropower plants offer significant potential for green house gas emision reduction and it is most ciritical to impove to forecast of changes in the hydrological regime caused by global warming related climate events [15]. Studies in hydropower plant projects are focusing on energy generation effectiveness.

Monteses et al. [16] researched the possibilities of short-term and medium-term forecasting of energy generation in hydropower plants using ANNs. Multilayer perception, long-short term memory and sequence to sequence models were used in the framework of ANN. They created a model for predicting energy generation based on data on past hydropower energy generation and precipitation.

Echtearm et al. [17] used hybrid deep learning model to predict hydropower generation. They created a model for forecasting production 1, 2 and 3 days ahead using convolutional neural networks.

Hannoon et al. [18] used different machine learning methods (ANN, Auto Regressive Integrated Moving Average and support vector machine) to predict power production. They used three scenarios: to forecast daily, monthly and seasonal generation.

Guo et al. [19] used ANN to analyze the impact of climate change on hydropower production, energy demand and greenhouse gas emissions. They used different climate scenarios for the analysis. Various socio-economic and meteorological parameters were used as input data. They believe that in the near and distant future, hydropower production will decrease and energy demand will increase, which will lead to a larger gap between hydropower generation and energy demand.

Optimized ANNs were also used in [20] for forecasting energy demand and hydropower generation and came to the conclusion that growth of both hydropower generation and energy demand can be observed based on climate change scenarios.

ANNs can also be used to research the hydropower potential of the river. This issue was investigated by Cai et al. [21] using Soil and Water Assessment Tools and ANNs for predicting hydropower generation and determining locations for the installation of small hydropower plants.

Cobner, Haktanir and Kisi [22] presented a practical way to predict the potential of electricity generation from hydropower plants using ANNs for the possibility of adding hydropower plants to the existing reservoir. The input data were inflows series, irrigation water requirements, evaporation rates, turbine running time ratios, while the output parameter was the value of the monthly energy generation. The model of ANNs was developed to estimate the monthly energy generation in the hydropower plant based on the data on the existing reservoirs.

Khaniya, Karunanayake, and Gunathilake [23] used ANNs to create a model for forecasting electricity generation at the Samanalawewa hydropower plant. The input data that were used were the amounts of precipitation at four measuring points near the hydropower plant. They concluded that the electricity generation in the observed hydropower plant will have a constant growth in the following period (until 2050), although the growth rate is not constant. They also stated that other meteorological phenomena such as temperature, air humidity, wind speed and direction affect the electricity generation.

Using ANNs Ceribasi and Ceyhunlu [24] created a model for short-term forecasting of electricity generation for two hydropower plants on the same watercourse. Data about the turbine flow, net head, efficiency and electricity generation were used to form the neural network model. Analyzing the obtained results, they concluded that there is a trend of decreasing energy generation in the observed power plants.

Hammid, Sulaiman, and Abdalla [25] researched the possibility of predicting the electricity generation of a small hydropower plant at Himreen Lake using ANNs. The work is based on the use of non-recursive ANNs with signal backpropagation for predicting hydropower plant performance based on turbine head and water flow over a 10-year time period. They find that ANN can predict power plant performance with a correlation coefficient (R) greater than 0.96. They concluded that formed model can successfully simulate and predict the operation of a small hydropower plant.

Lopes et al. [26] studied the possibility of predicting the monthly potential of energy generation in hydropower plant using ANNs. In their paper, they used two different approaches to predict electricity generation: polynomial neural networks and conventional ANNs. The input data for the formation of the model is precipitation. They concluded that by using artificial intelligence techniques it is possible to model the dynamic, seasonal and non-linear behavior of the studied problem.

In order to achieve effective management of hydropower reservoirs, it is necessary to understand the interactions that exist between reservoir characteristics and energy generation.

Abdulkadir et al. [27] presented modeling of variable storage characteristics for two hydropower plants along the Niger River for power generation using ANNs. As input they used data of reservoir inflow, storage, reservoir elevation, turbine release, net generating head, plant use coefficient, tail race level and evaporation losses and energy generation data as output. Monthly data on the characteristics of the accumulation were used to train the network. The formed model for Kainji and Jebba reservoirs achieved good production prediction values with correlation degrees of 0.89 and 0.77.

In their article [28], Abdulkadir, Sule and Salami formed a neural model for reservoir management along the Niger River. Based on the different characteristics of the reservoir a neural model was created for the optimal discharge from the reservoir. Monthly data on reservoir inflow, turbine release and losses due to evaporation were used as input data for training neural networks. The paper concluded that neural networks are a reliable tool for predicting different characteristics of accumulation.

Thus, Gaffar and Aisjah [29] studied the possibility of predicting the load required for generation planning and power system operation. They stated that the most popular tools for predicting electric load are ANNs with a back propagation. In their research, the input data for forming the network were the mean value of temperature and air humidity. The output data was average system load.

3.2 PV power forecasting using ANNs

PV power forecasts are increasingly crucial for planning, managing and controlling integrated energy systems [30].

Most studies in this field have focused on investigating direct PV power forecasting as it can achieve accurate forecasting of PV power generation [31].

Since 2016 PV solar has been the technology with higher growth [32]. ANNs are the most used apparatus learning technique in solar irradiance, temperature and PV power output forecasting [33].

As more PV power generation systems are integrated into the energy grid the problem of handling with uncertainties like changes in solar irradiation, humidity, dust in the air, wind speed and temperature make it challenging to accurately predict the power output [34].Shen et al [35] introduced and analyzed the variations of atmospheric conditions and solar irradiance in order to determinate the optimal tilt angle in photovoltaic power plant.

Khatib developed [36] a ANN model to predict a clearness index. The neural network adopted was FNN, among the most commonly used neural networks that learns from example. The performance of ANNs was assessed using MAPE, MBE and RMSE.

Table 2. shows some more ANNs models works related to photovoltaic forecasting.

Table 2. Selected related works of photovoltaic energy production forecasting

Reference	Input variable	Output variable	Approach to develop forecasting
[13]	The ambient temperature, cell temperature and solar irradiance	Energy production	ANN models: Feedforward (FNN), Multi-Layer Perceptron (MLP), Long-short term memory (LSTM) and Modular model
[36]	Latitude, longitude, day number, sunshine ratio	Clearness index	Feedforward Artifcial Neural Network (FNN)
[37]	Air Temperature, Relative Humidity, Surface Pressure, Wind Direction, Wind Speed, Month, Day and Hour	Global Horizontal Irradiance	FeedForward Artifcial Neural Network (FNN)
[38]	Temperature of air, Time, Humidity, Wind speed, Atmospheric pressure, Direction of wind and Solar radiation data	Solar radiation	Multi-Layered Perceptron (MLP)
[39]	Minimum, Average and Maximum temperature values, Relative humidity, Minimum, average, maximum wind speed and Precipitation amount.	Daily production	Feedforward Artifcial Neural Network (FNN)
[40]	Historical numerical weather predictions and weather measurements (incident global irradiance, ambient temperature, relative humidity, wind direction and speed, solar azimuth, elevation angles.	PV power	Artificial neural networks, K-means clustering, linear regressive correction method
[41]	Weather paremeters	Power output	MLP
[42]	Temperature, previous power production	PV power	Multi-Layer FNN
[43]	Solar data	Power output	MLP
[44]	Weather and real time system performance	Power output	ANN and Levenberg-Marquardt method
[45]	Solar irradiation, ambient air and module temperature, wind speed, and relative humidity	Power generation	ANN and Levenberg-Marquardt method
[46]	Atmosphere conditions	PV power generation	ANN and gray wolf optimization

[47]	Location, temperature and irradiance levels	System performances	Extreme Gradient Boosting, Gradient Boosting Machine, recurrent neural networks and ANN
[48]	Wind speed, module temperature, ambiance and solar irradiation	PV plant power output	ANN, Support Vector Regression, Recurrent neural networks
[49]	Sky images, weather data	PV power	ANN, long short-term memory and the gated recurrent unit
[50]	Cloudiness, solar radiation	PV energy production	Autoregressive Integrated Moving Average and ANN
[51]	Weather data	PV power	Support Vector Regression and ANN with different Metaheuristic Optimization Algorithms
[52]	Temperature, dew point, wind speed, cloud cover, relative humidity and pressure	PV generation	ANN with different combinations

4 CONCLUSION

Renewable energy and various machine and deep learning methods, such as ANNs, are considered as very important technologies for the future of energy systems. In this paper we have reviewed the literature on the applications of ANNs in hydropower and photovotaic power systems. The folowing concluding remarks can be drawn from this study:

- Development of renewable energy technologies present good alternative to conventional energy generation.
- ANNs models have a high success rate in predicting energy in photovoltaic and hydropower plant projects.
- The most used neural network in analyzed articles were FNN as this is the most communly used neural networks that learns frome example.
- In the hydropower plants, ANNs are most commonly used to predict energy production based on meteorological data (such as precipitation and temperature) and water inflow data.
- In PV solar power plants, ANNs are mainly used for short- and medium-term forecasts in both direct and indirect forecasts. Direct forecasts involve predicting power output or energy production, while indirect predictions are based on predicting solar radiation.
- In some papers, other ML methods have been used in addition to ANNs for optimization of the results.

Most of these studies reported advantages of ANNs in modeling these projects such as high accuracy, the use od ANNs avoids complicated mathematical models etc. It was also observed that ANNs models are widely used in sustainable energy forecasting projects.

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