Forecasting Wind and Solar Energy Production in the Greek Power System using ANN Models

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Abstract: - Renewable energy sources (RES) like solar and wind are quite uncertain because of the unpredictable nature of wind and sunlight. As a result, there are at present several issues with system security and the transformed structure of the energy market due to the increasing utilization of renewable energy sources (wind and solar). Accurate forecasting of renewable energy production is extremely important to ensure that the produced energy is equal to the consumed energy. Any deviations have an impact on the system's stability and could potentially cause a blackout in some situations. The issue of the high penetration of RES is discussed in this study along with a novel method of predicting them using artificial neural networks (ANN). The SARIMA prediction model is contrasted with the ANN approach. The suggested ANN for wind power plants has a mean average prediction error (MAPE) of 3%–4.3%, whereas the SARIMA model has a MAPE of 5%–6.5%. In comparison, the present prediction approaches typically have a MAPE of 5%–10%. When the MAPE of solar power plants was calculated, it was also discovered that the SARIMA model had a MAPE of 2.3%–4% and the suggested ANN had a MAPE of 1.4%–2.3%, whereas the MAPE of the present prediction methods was often about 9%.

Key-Words: - artificial neural networks; distribution system; renewable energy sources forecast; power production; solar and wind energy production; transmission system.

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1 Introduction

The shortage of fossil fuel resources, [1], [2], as well as global strategic incentives to reduce carbon emissions in the environment, have led to the high penetration of renewable energy sources (RES), where wind and solar energy are crucial in this process, [3], [4], [5]. For the stable operation state of the power system there is a need for accurate forecast of the load, [6], [7], and the RES production. RES production is varying in time, as the weather processes on which it is dependent (solar radiation and wind speed) are also variant and difficult to be predicted. By aiding balance, accurate forecasting can help prevent the severe fluctuations that could be created in the power grid, [8], [9], [10], [11], and it can even cause a major blackout with an enormous impact on society and the economy, [12], [13], [14].

Numerical weather prediction (NWP) tools, [15], which originated in meteorology and were directed to the energy sector after a couple of decades, have been developed because of collaborations between electrical engineering and meteorology. The aim of this collaboration was for these NWP models to cover the needs of the energy sector. These models are used to forecast wind, along with algorithms that give a non-linear transfer of wind speed into power while also considering other relevant meteorological and orographic influences, as well as wind turbine type and/or wind farm architecture, including shadow impacts. Grid operators employ such forecasts for intraday and near-real time grid operations, [16], day-ahead market clearance checks (24h), [17], and operational planning (many days ahead) depending on the forecast time horizon, [18].

In terms of RES forecasting, deterministic and probabilistic methodologies can be distinguished, [19]. In a deterministic technique, the variable to be forecasted is estimated with a specific value for each subsequent time step. A probabilistic strategy emphasizes providing information about the entire spectrum of likely power generation events, through a set of alternative scenarios or a collection of conditional probability density functions (PDFs). For example, ensemble models, that a model runs numerous times from radically altered initial conditions, [20], or statistical techniques, [21], can provide the basis for probabilistic predictions. This gives information about the predicted uncertainty impacting every single value forecast as well as a prediction about the probability of the occurrence of a specific event. While renewable energy forecasting based on deterministic approaches has been studied for almost three decades, probabilistic forecasting has only recently attracted attention. It is currently becoming more common, particularly in wind energy.

Following the first published work on wind energy forecast, [22] many research works have been published on the subject in the following decades. The most representative ones in wind power forecasting are in [23], [24], while, [25], [26], [27], discuss a range of the most current uses for deterministic and probabilistic wind power forecasting.

In terms of solar energy forecasting, the first published paper is found in [28]. [29], [30], give thorough assessments of the state of solar irradiance forecasts for energy generation throughout a range of time periods, whereas, [31], [32], examine and compare several forecasting strategies to anticipate solar power output. In [33], along with these references, it is offered an interesting overview of a variety of forecasting techniques as well as statistical and computational intelligence models, with a focus on forecasting electricity prices. In terms of comparing forecasting models and approaches, [34], [35], [36], offer an insightful investigation of the progress that has been made in terms of wind power forecasting.

Plenty of researchers have examined the use of AI algorithms for solar radiation forecasting, which is a key factor affecting solar systems' output power, [37]. In [38], researchers found that ANN was the most useful method for estimating solar radiation when compared to other methodologies. In [39] it was discovered that the Gradient Boosting Tree (GBT) model performs better than other approaches regarding both precision as well as accuracy when estimating solar radiation. In [40], the authors proved that all the machine learning systems they evaluated could accurately forecast daily solar radiation data; the ANN method performed the best. Wind energy development uses Machine Learning (ML) and Deep Learning (DL) algorithms, just like solar energy does. Wind speed data and other pertinent information are used in this process. [41], presented hybrid SVM models and argued that the Support Vector Machine (SVM) model was better than other models. To improve predicting accuracy, Xiao proposed employing a self-adaptive Kernel Extreme Learning Machine (KELM), [42].

There is research interest in the short-term prediction of RES presented in the current work for the following reasons. Firstly, while there have been many publications on load forecasting, the same has not been done on the forecasting of energy production from RES. Secondly, this gap is particularly major regarding the Greek electricity system, which has a particularly high share of installed capacity in wind and photovoltaic plants. This becomes especially necessary given that due to the policy implemented by the European Union and the Greek governments, the size of RES will increase in the coming years (approval has already been given for the first offshore wind farms in the Aegean Sea), [43], [44], and Greece will become an exporter of green energy to Europe (with the new cross-border connections approved to be implemented), [45].

The main concern of this research work is the development and future implementation in the power systems of a prediction method for wind and solar power production. This prediction method is based on Artificial Neural Networks (ANNs) and it is applied to solar and wind power parks in the southern region of Greece. The contribution of this methodology has to do with the exact prediction that it gives, proving its efficiency with other prediction methods. Its outcome is even more significant taking into consideration that it will be a valuable tool for both the Transmission System Operators (TSOs) and the Distribution System Operators (DSOs), especially in Greece, where the penetration of RES will increase and the demand for an accurate prediction of the power produced by RES (wind and solar) will be vital for the power system's stability.

The proposed ANN methodology implementation has advantages such as scalability, interpretability, and the ability to capture non-linear relationships such as power production from solar or wind. Also, ANNs have the ability to perform many calculations simultaneously, which allows them to process large amounts of data quickly and efficiently, as data from wind or solar power plants. From this study, it was found that the accuracy of the ANN model improved the performance of the power system. Also, the proposed ANN has a fault tolerance, needed in the prediction of the RES production. Corruption of one or more cells of an ANN does not prevent it from generating output, making ANNs with this feature fault tolerant, since there is corrupted data from the Supervisory Control And Data Acquisition (SCADA), from where the input data are collected. The main reason for applying ANNs to our research is that ANNs can store information on the entire network. Therefore, the disappearance of a few pieces of information in one place does not prevent the network from functioning. Also, ANN is selected because of its ability to learn and use a non-linear relationship to map several input parameters to an output parameter.

The structure of this work is as follows. In Section 2, the proposed methodology using ANNs that estimates the power production from solar and wind parks is presented. Section 3 includes the results of the proposed methodology, and a comparison between the forecasted and the exact production is presented. The concluding notes are provided in the last section.

2 RES Production Prediction

In this section, the ANN method for the prediction of power production from RES is presented. There is also a short introduction to the SARIMA prediction model and, finally, a comparison between these two different prediction methods, proving the better performance of the ANNs.

2.1 ANNs and RES Production Prediction

What is already quite well known about ANNs is that they represent a relatively young technique that is based on machine learning principles, [46], [47], [48]. It is a technique designed to determine the optimal system output given a predetermined set of high-quality input data that are necessary to guarantee the ANN algorithm operates as intended. This algorithm is usually used when it is challenging to determine how the input and output values relate to one another. To determine that transfer function, the ANN algorithm uses a similar principle as the human nervous system for learning and implementing the experiences from the past for the new tasks, [49], [50], [51], [52]. The human nervous system contains many neurons that process information and communicate with one another through synapses. Basically, what happens there is that each of the neurons that receives some data processes it and then determines if it will forward it to other neurons to which it is connected and, if it will, to which of those neurons. ANN, on the other hand, represents the mathematical model of this system, formed out of the artificial neurons that transfer the information among themselves, and then, by trying to find the impact that each piece of information has on the outcome of the problem, proposes a solution of the analyzed problem based on the defined set of inputs.

Figure 1 depicts the mathematical representation of a neuron in an ANN. Synapses connect the inputs that each neuron receives to that neuron. These inputs may come from the outside world or from the neurons in the previous layer. In Figure 1, x_j represents j input, j=1,..,n. The synapses' strength is defined through synaptic weight ω_{ij}, where excitatory synapses are represented by a positive value of ω_{ij}, and inhibitory synapses by a negative value. After multiplying the transfer function by the appropriate weight coefficients on all inputs, the output is integrated and compared to the threshold value. The activation value would be 1 if the transfer function exceeded the threshold, otherwise it would be 0. Formally, it can be expressed as follows:

$$\phi = \phi(\textstyle\sum_{j=1}^{n} x_j \cdot w_{i,j} - \theta_j) \quad (2)$$

The sigmoid function, which is described by (3), is the most frequent activation function of a neuron.

$$o_j = \frac{1}{1+e^{-\alpha\cdot\phi}} \quad (3)$$

However, what can be raised as the first problematic point here is the matter of determining the weighting factors that would be assigned to each of the input values to obtain the result of maximal accuracy. To resolve this issue, the mechanism can be established in cases in which both the input data and the measured output values are known. If that is the case, the neuron can be fed by the input data, after which the obtained output could be compared to the already available measured output value. Based on the difference between the calculated and measured values, the weighting factors can be modified to improve the precision of the described activity of the neuron. This process is iterative and can be repeated until there is sufficient accuracy (usually decided by the difference being low enough). The schematic of is shown in Figure 2 below.

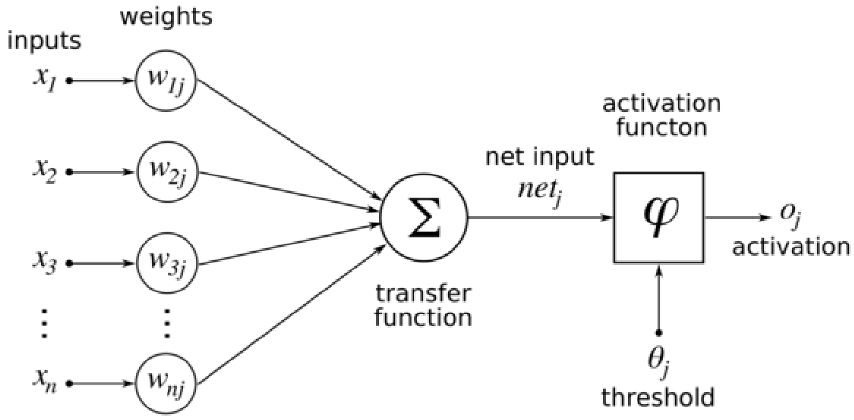

Fig. 1: An ANN's mathematical representation of a neuron

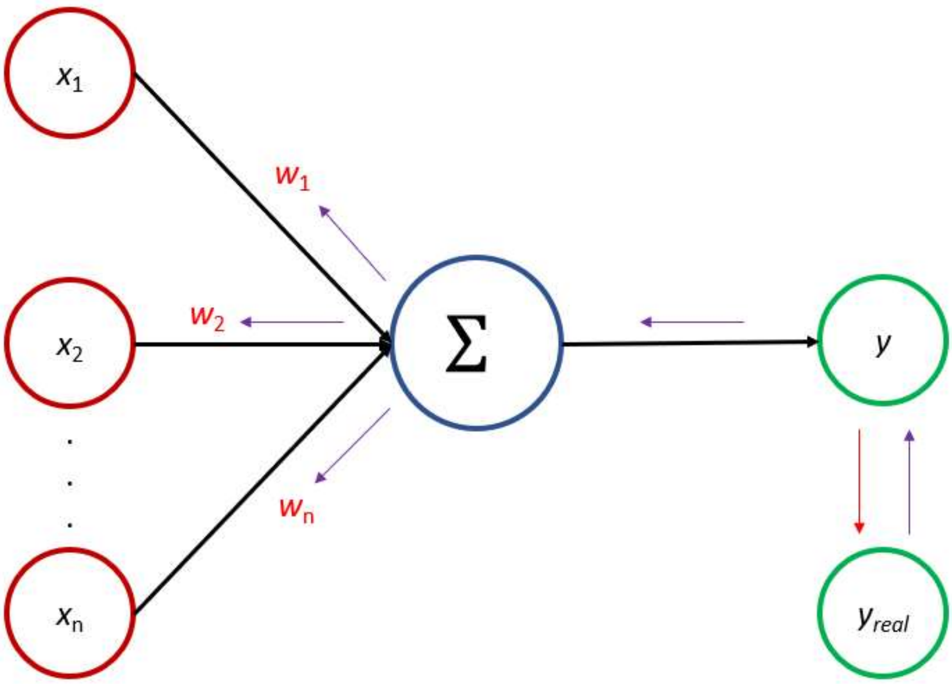

Fig. 2: Weighting factors tuning for the single neuron

The same logic can be applied to the layers, in which the neurons are grouped in the ANN. Usually, there are three types of layers, as can be seen in Figure 3: the input layers, the hidden layers, and the output layers. The first layer of the ANN is typically the input layer, with the only purpose of transmitting the signals further. The output layer is the final layer in an ANN. Its goal is to establish the overall ANN's outcome. The number of hidden layers, which compose the ANN and affect its accuracy, forms the pathway between the input and output layers. When the described method of determining the weighting factors is applied to the entire ANN instead of the single neuron, it is called "back propagation", as shown in Figure 3.

This process of deciding the weighting factors in the entire ANN is called the training of that ANN. To pull that off properly, the algorithm needs to be fed quite a large amount of input data, followed by the accompanying known output values. Meteorological data is what is most relevant for wind and solar power plants because the production power of those sources is directly related to that kind of data. To improve the prediction further, the initial database used for training has also been processed by adding a new entry for the seasons (summer, winter, autumn, and spring) and for the time of day (night or day). In this way, the ANN was enabled to recognize the patterns to predict the production even better. The dataset used for the training came from real-life measurements of the chosen weather and power system parameters for the current work. Training took up most of that dataset. Also, one smaller part of the dataset ended up being used for testing, and another one was used for the validation of the developed ANN.

Three phases contribute to the ANN's training and testing process using the MATLAB neural network toolbox to train and develop neural network models. The training data is selected from the whole set of available data. 70% of the database is utilized for training, 15% is used for testing, and 15% is used for validation. These database events were produced and selected at random. This is very important because a uniform part of the base can lead to wrong conclusions. Next, to prevent saturation, the data is normalized. The back propagation algorithm has been used to train the artificial neural network.

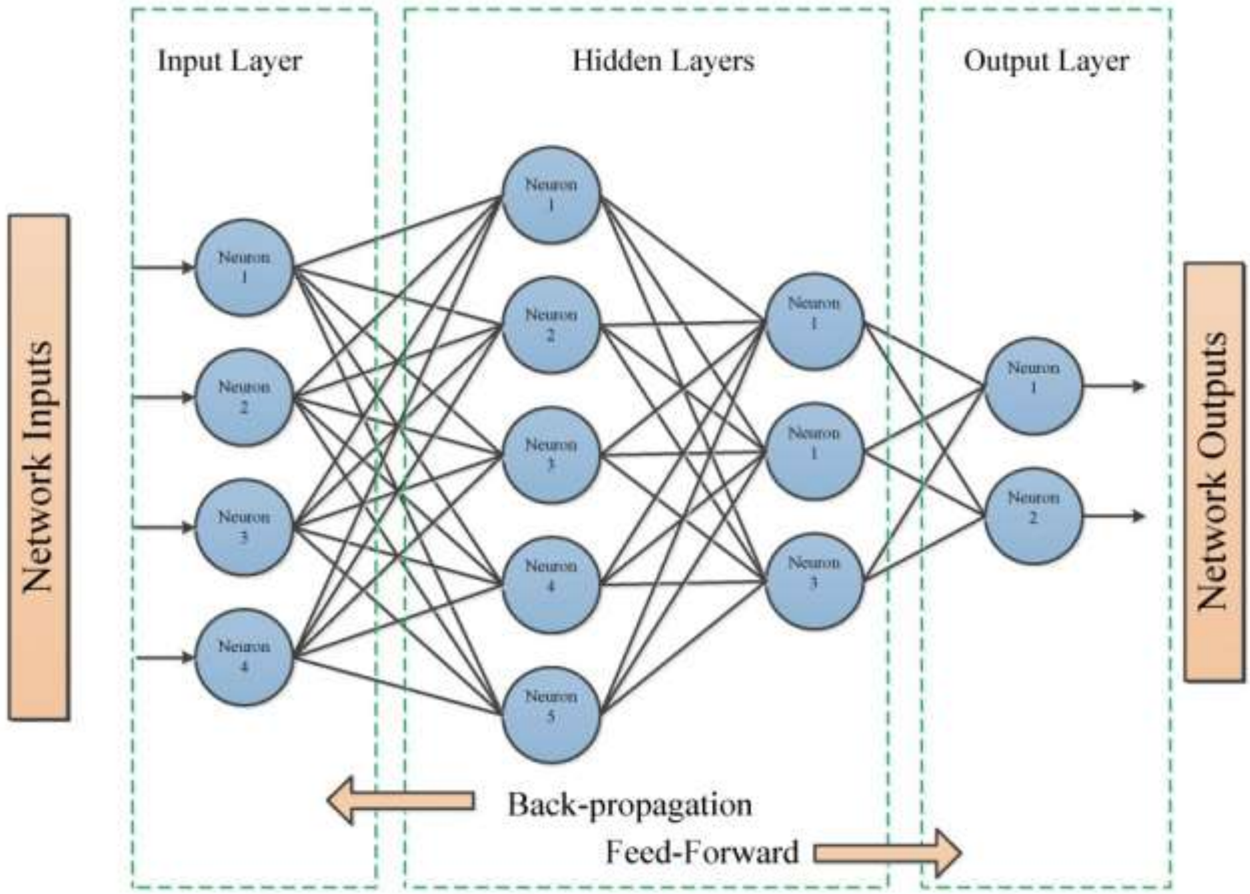

Fig. 3: Back propagation method of ANN training

In order to evaluate the prediction capability of the created ANN model, the parameter known as MAPE (Mean Average Prediction Error), was used, [53]. For the maximal precision of the created ANN, this parameter, calculated based on the results of the ANN and the measured values for the same set of input data, needs to be as small as possible. The difference between the measured and predicted value for the relevant period is what first calculated as the forecast or residual error (E):

$$E_t = Y_t - F_t \tag{4}$$

where E_t denotes the variable's period t forecast error, Y_t is the variable's period t measured value, and F_t denotes the variable's period t forecast variable. The accuracy metrics are dependent on the size of the variable because the forecast error E_t is on the same scale as the data. The Mean Absolute Percentage Error (MAPE) is calculated in equation (5), to compare forecast performance between different datasets.

$$MAPE = 100 \cdot \frac{\sum_{t=1}^{N} \left| \frac{E_t}{Y_t} \right|}{N} \tag{5}$$

The best way to achieve minimal error in the prediction of some power plant production is to have a good and well-organized database. The better input data gives better performance for ANN and better production prediction. Meteorological data are the most important for wind and solar power plants because they appear in the physical models of these renewable energy sources. To improve the prediction, the database is further processed by adding an entry for the seasons (summer, winter, autumn, and spring) and time of day (night or day). Also, it was tried to present ANN output and productions binary code, but this was unsuccessful. The next way to decrease the MAPE is to get the production from the same hour from the previous day and to get the production from the previous hour as inputs.

The database consists of data from 1 January 2018 up to 1 March 2023 (45,242 hourly data) for solar and wind power plants placed in Southern Greece, presented in Table 1. The meteorological data for Wind Power Plants (WPPs) are organized as: wind direction and wind speed and temperature. The meteorological data for Solar Power Plants (SPPs) are organized as: Global horizontal irradiance, temperature, and wind speed.

In Figure 4 the flowchart of the classification process is depicted. From validation data, the optimal ANN hyperparameters are determined: network architecture, types of activation functions, regularization parameter, optimal moment for the end of training, etc. It is not possible to learn hyperparameters from a test set since this would result in inconsistent results when estimating network performance. Cross-validation is the process of learning hyperparameters by training the network for several combinations of hyperparameters on training data and measuring performance on validation data. The optimal combination of hyperparameters is determined by observing which combination yields the greatest results on the validation data. The measure of performance for the cross-validation procedure for regression problems may be the standard deviation. The maximum number of hyperparameters is determined by the range of the output variable (production WPP or SPP) and the number of input parameters and the size of the database of the training data set. Then the same number is distributed among the layers and the number of neurons in the layers. The optimal result is obtained based on experiential variation and in accordance with the minimization of the error (MAPE) on the test set. It starts with the maximum number of neurons in a smaller number of layers and comes to the decision that an ANN with more layers and a smaller number of neurons is better for predicting WPP and SPP. Of course, each power plant represents an ANN model with adjusted hyperparameters for itself.

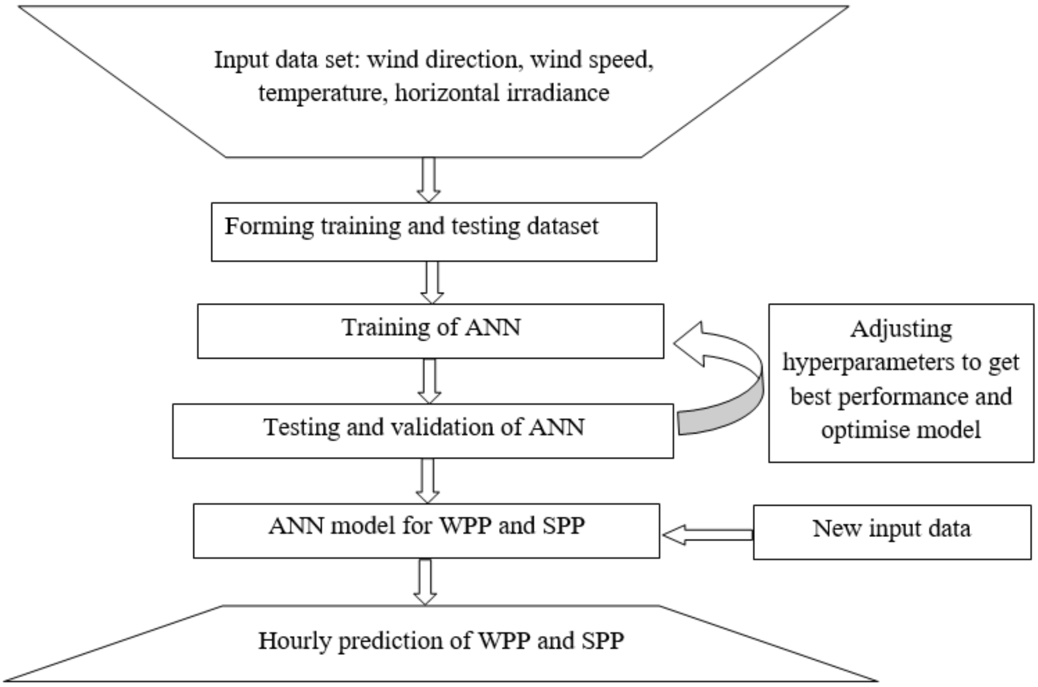

Fig. 4: Flowchart of the classification process

Table 1. Solar and Wind Power Plants in selected regions of Southern Greece

Substation Name1	Installed Capacity [MW]	Type of power plant
SPP-1	2.188	Solar
SPP-2	4.9	Solar
SPP-3	6	Solar
SPP-4	9	Solar
SPP-5	11.963	Solar
WPP-1	7.65	Wind
WPP-2	13.6	Wind
WPP-3	18.4	Wind
WPP-4	28.85	Wind
WPP-5	43.7	Wind

For reasons of information confidentiality, the names of the power generation substations are given coded and not with their actual names.

2.2 The SARIMA Prediction Model

The ARIMA model analyzes historical data, dividing it into three components: autoregressive (AR), integrated (I), which denotes linear or polynomial trends, and moving average (MA), which denotes a weighted moving average over prior mistakes, [54], [55], [56], [57], [58]. In order to create the ARIMA(p, d, q) model, it combines the three model parameters AR(p), I(d), and MA(q).

p = AR order
q = MA order
d = I order (differencing)

The multiplicative Seasonal ARIMA model namely SARIMA is a variant of the standard ARIMA model. It is typically written as SARIMA(p,d,q)(P,D,Q), where, p, d, q and P, D, Q are positive integers that refer to the polynomial order of the AR, I, MA parts of the seasonal and non-seasonal components of the model, respectively. This is done to account for the wind speed and the irradiation, which have a seasonal effect. The SARIMA model is described mathematically in (6).

$$\varphi_P(B)\Phi_P(B^s)\nabla^d\nabla_s^D x_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \quad (6)$$

Where: x_t is the predicted variable (i.e., wind speed), $\varphi_P(B)$ is the regular AR polynomial of order p(), $\theta_q(B)$ is the regular MA polynomial of order q(), $\Phi_P(B^s)$ is the seasonal AR polynomial of order P(), $\Theta_Q(B^s)$ is the seasonal MA polynomial of order Q, ∇^d is the differentiating operator that eliminate the non-seasonal non-stationarity, ∇_s^D is the seasonal differentiating operator that eliminate the seasonal non-stationarity, B is the backshift operator, making the observation at a specific shift in time xt (i.e. $B^k(x_t) = x_{t-k}$) and finally ε_t determines the seasonal period and is subjected to a white noise technique. These polynomials are explained in (7-12):

$$\theta_q(B) = 1 - \sum_{t=1}^{q} \theta_t B^t \quad (7)$$

$$\theta_Q(B^s) = 1 - \sum_{t=1}^{Q} \Theta_t B^{s,t} \quad (8)$$

$$\varphi_p(B) = 1 - \sum_{t=1}^{p} \varphi_t B^t \quad (9)$$

$$\Phi_p(B^s) = 1 - \sum_{t=1}^{P} \Phi_t B^{s,t} \quad (10)$$

$$\nabla^d = (1 - B)^d \quad (11)$$

$$\nabla_s^d = (1 - B^s)^D \quad (12)$$

The Akaike Information Criterion (AIC) is a statistic used to compare models to determine which one best fits the data. The AIC penalizes some models for complexity while rewarding those that fit the data well. It could be written as:

$$AIC = 2k + \ln\left(\frac{RSS}{n}\right) \quad (13)$$

with n being the overall number of observations equal to 168, k being the number of free parameters and RSS is the residual sum of squares. At last, the forecasting of the intended period can be carried out utilizing the obtained valid model. Once the model was formulated, it was used to predict wind speed and solar radiation for the 1st of July 2023 to the 7th of July 2023 (the same time period as the proposed ANN). To evaluate the models' accuracy, the statistics for the 168-hour forecasting outcomes are then averaged.

The next section contains the results obtained by using the developed ANN method in comparison to the SARIMA prediction model, particularly focused on the prediction of the power production of wind and solar power plants in the selected regions of southern Greece.

3 Forecast Improvement Results

The results given in this section have been obtained by using both the developed ANN and the SARIMA model for the forecast of the production of renewable energy sources, considering the time horizon of 168 hours into the future. This kind of generation power forecast has been done for the period from the 1st of July 2023 to the 7th of July 2023, allowing its further comparison with the actual measured values of the same parameter. During this analysis, 10 separate renewable energy sources have been taken into consideration, as presented in Table 1.

The obtained findings are crucial for the rest of the demonstration outcomes, as they provided an unprecedentedly accurate base for further investigations of their application in congestion management, mFRR and aFRR dimensioning and activations, as well as among the additional enhanced transmission and distribution system planning and operation procedures connected to weather forecasts. For the sake of easier understanding, the results will first be shown for the five considered wind power plants and then for the five solar power plants that were considered.

3.1 Results for the Wind Power Plants

Table 2 gives a comparison of the results obtained by the ANN forecast and the SARIMA model compared to the actual production values of the wind plants. MAPE has been calculated for each of the 168 hours for each of the WPPs. By that, it was calculated that the average MAPE for WPP-1 to WPP-5 was approximately between 3% and 4.3% for the proposed ANN methodology, while for the SARIMA model MAPE was approximately between 5% and 6.5%. As a benchmark, the MAPE of WPP forecasts (market schedules) using GA, [59] or Deep Learning, [60], is typically around 9% and 7% respectively, highlighting the improvement made by the usage of ANN methods. The optimal ANN structure is with 5 layers with number of neurons: 30 20 10 10 10. More layers lead to over fitting and increasing the error.

Table 2. Obtained results for the wind power plants

Substation Name	MAPE [%]			
	ANN	**SARIMA model**	**GA [59]**	**DL [60]**
WPP-1	3.02	4.92	≈9	≈7
WPP-2	3.27	6.31		
WPP-3	3.68	6.52		
WPP-4	4.16	5.83		
WPP-5	4.28	6.39		

To make the examination of the results easier for the reader, those results have been used to create diagrams, on which the exact measured production power is given in blue, whereas the ANN forecast results, and the SARIMA model are shown in red and purple, respectively. These diagrams for the substation names presented in Table 1 can be seen in Figure 5, Figure 6, Figure 7, Figure 8 and Figure 9. A brief observation of the three curves shown for WPP also indicates that the results of the ANN forecast matched the measured production values well, thus confirming the assumption of ANN being able to significantly improve the quality of the WPPs' power forecast.

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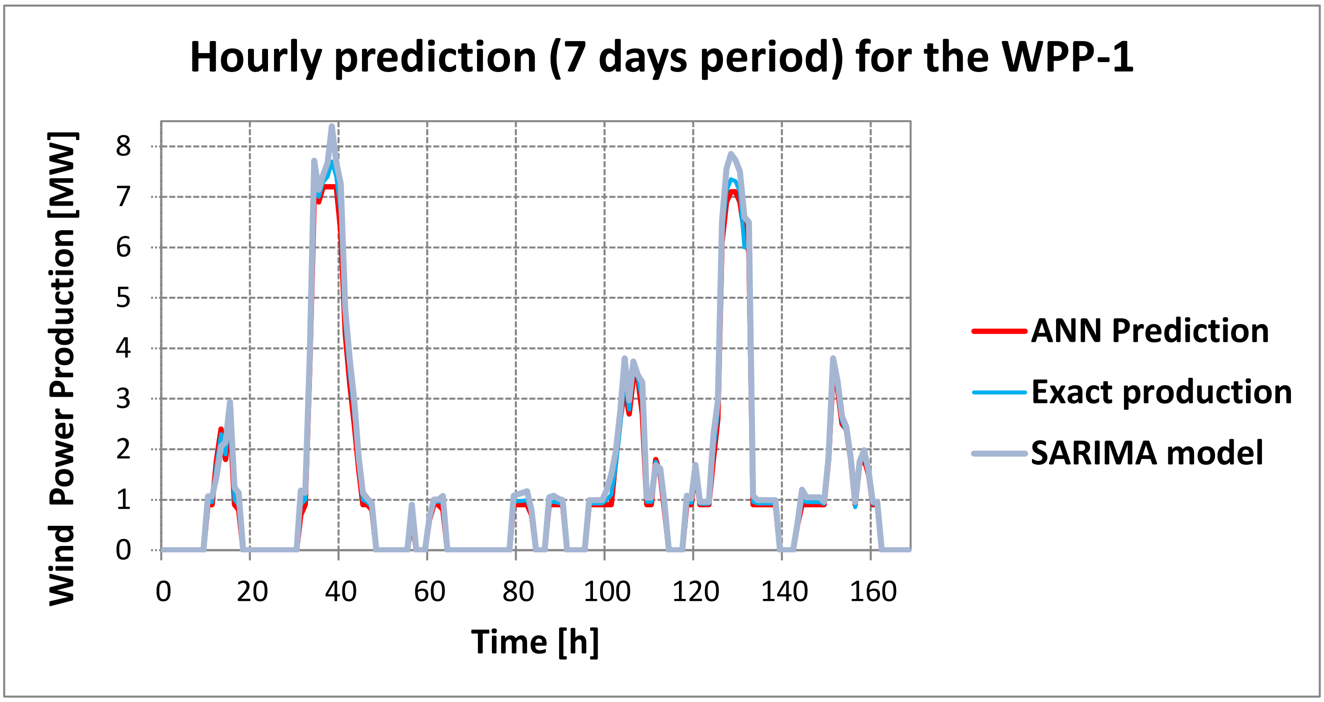

Fig. 5: Comparative analysis (7-days period) for WPP-1

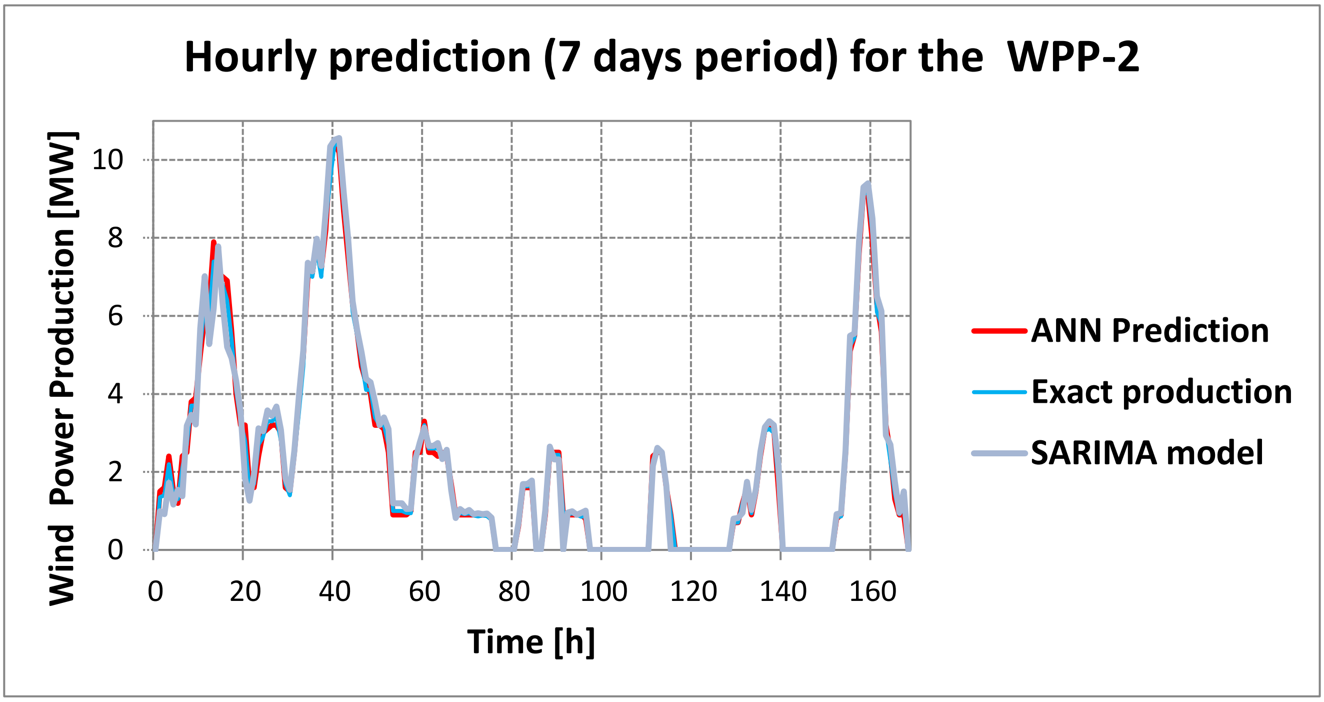

Fig. 6: Comparative analysis (7-days period) for WPP-2

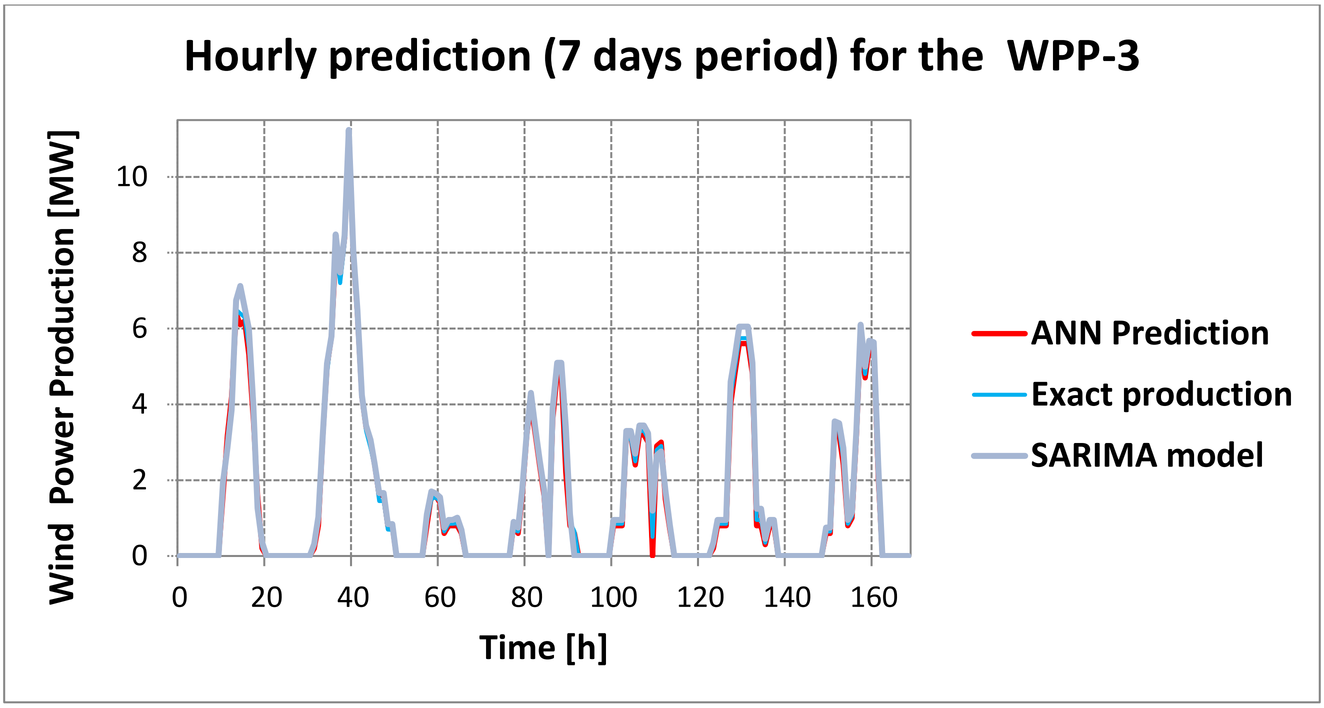

Fig. 7: Comparative analysis (7-days period) for WPP-3

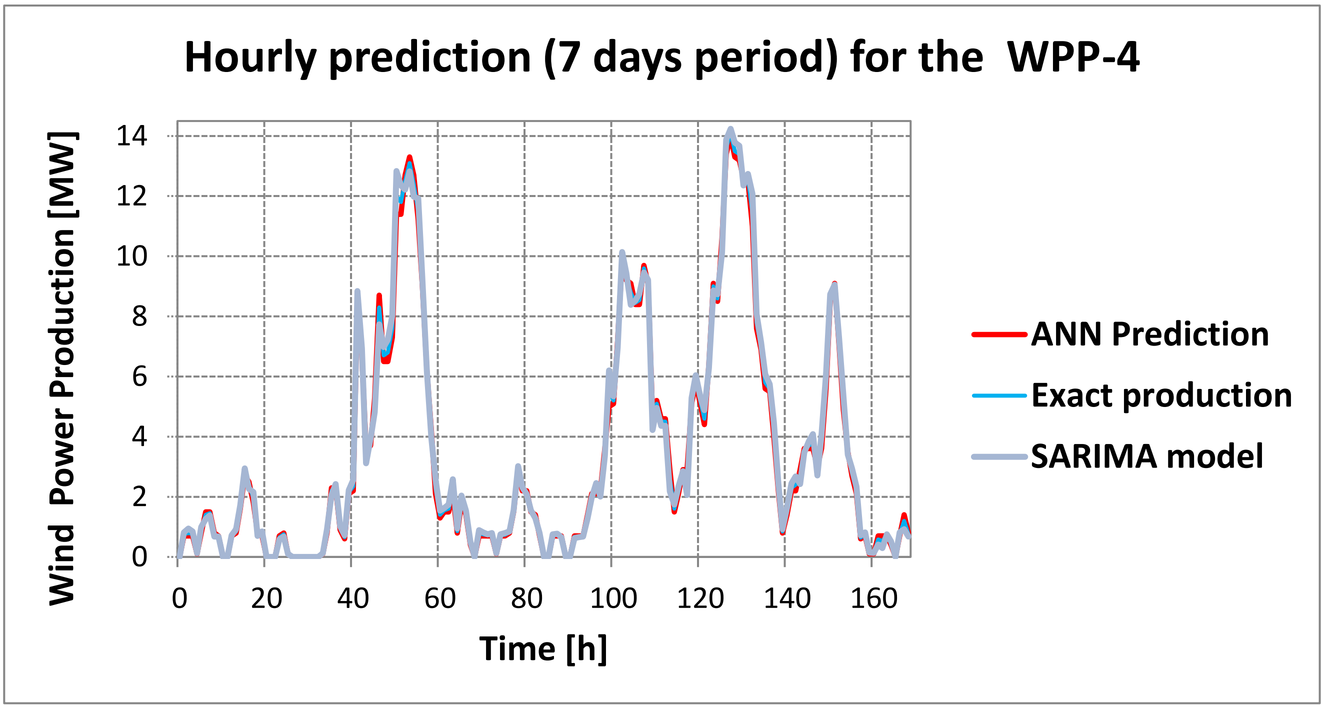

Fig. 8: Comparative analysis (7-days period) for WPP-4

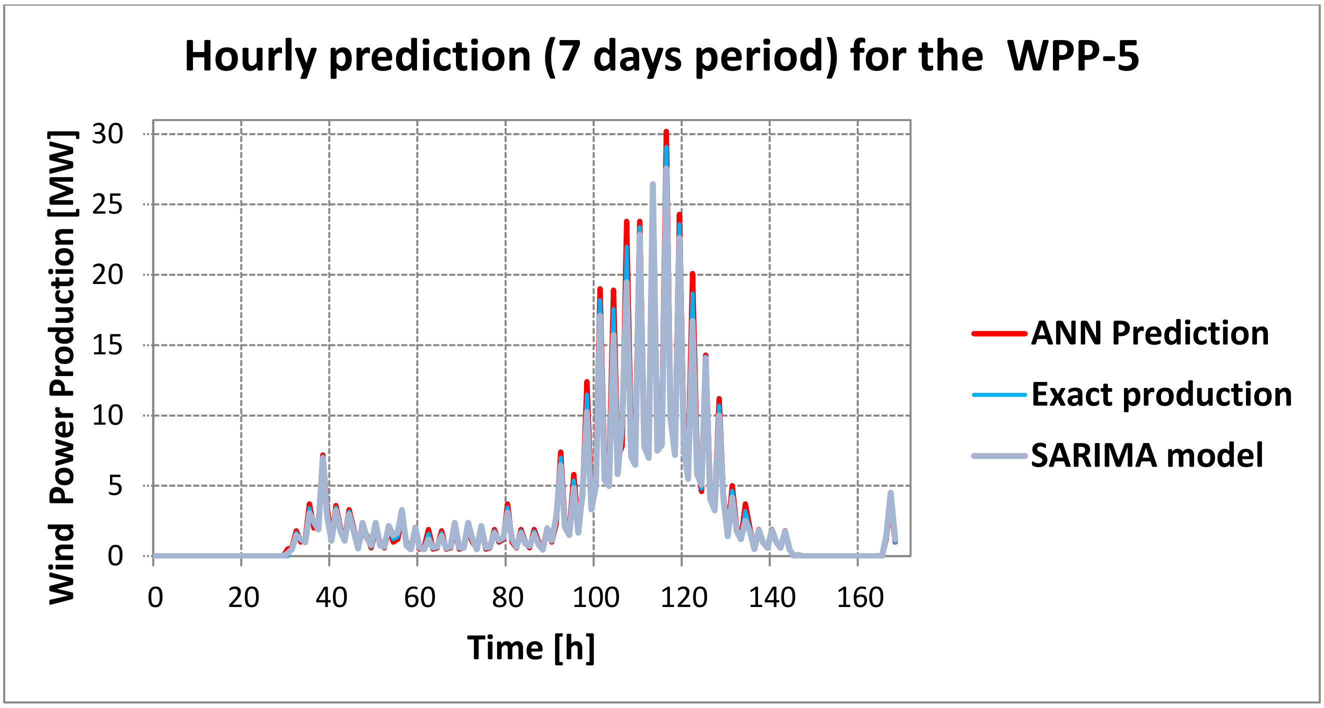

Fig. 9: Comparative analysis (7-days period) for WPP-5

3.2 Results for the Solar Power Plants

Table 3 gives a comparison of the results obtained by the ANN forecast and the SARIMA model compared to the actual production values of the solar plants and other AI techniques. MAPE has been calculated for the 168 hours for each of the SPPs, both for the ANN forecast and the SARIMA method as well. From the aspect of energy balancing and long-term plans, ANN provided very good results and was better than the SARIMA model. ANN can monitor the changes in production more accurately and therefore generate a more realistic production plan for solar power plants than any of the classic planning methodologies. Figure 10, Figure 11, Figure 12, Figure 13 and Figure 14 give the same level of insight but cover the exact and forecasted production power values for the 5 SPPs. The smallest error MAPE of 1.39% and it is achieved for a structure with 3 layers with 60, 30 and 20 neurons per layer.

Table 3. Obtained results for the solar power plants.

Substation Name	**MAPE [%]**			
	ANN	**SARIMA model**	**GA [59]**	**DL [60]**
SPP-1	2.28	3.20	5-10	5-10
SPP-2	1.66	3.95		
SPP-3	1.39	2.26		
SPP-4	1.85	2.70		
SPP-5	1.92	3.21		

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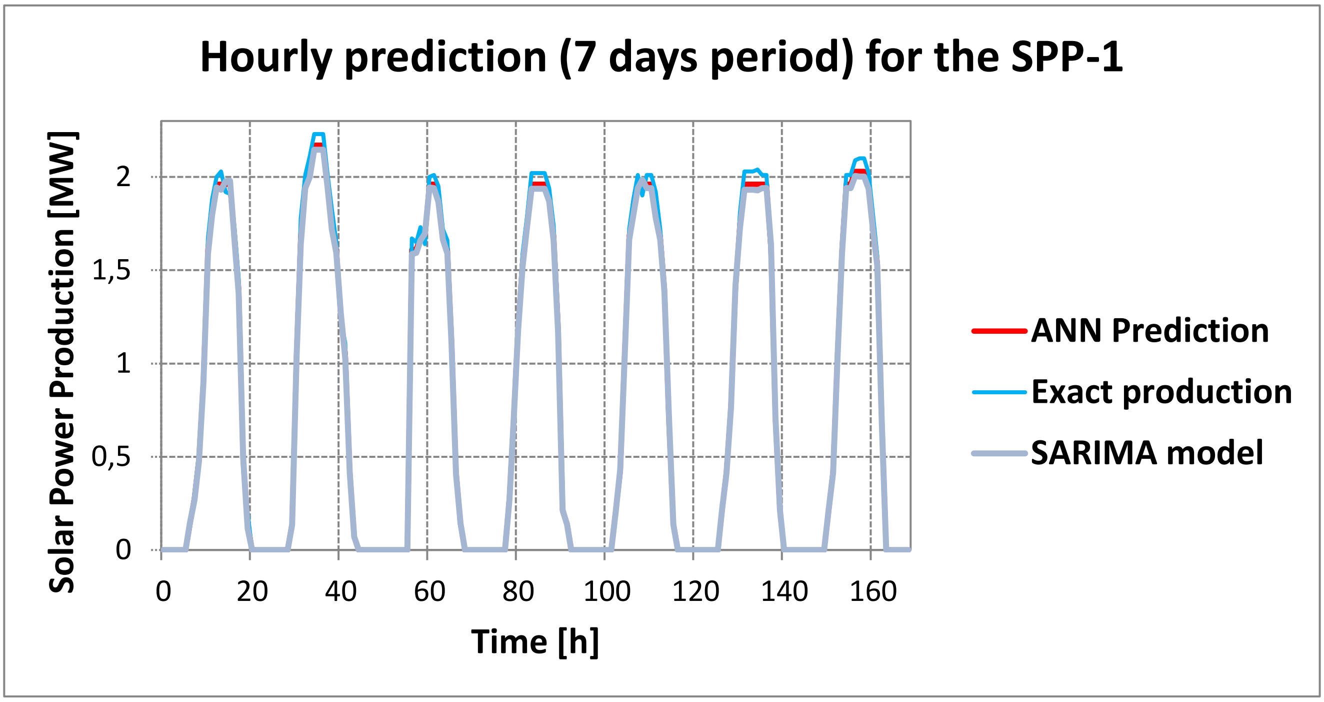

Fig. 10: Comparative analysis (7-days period) for SPP-1

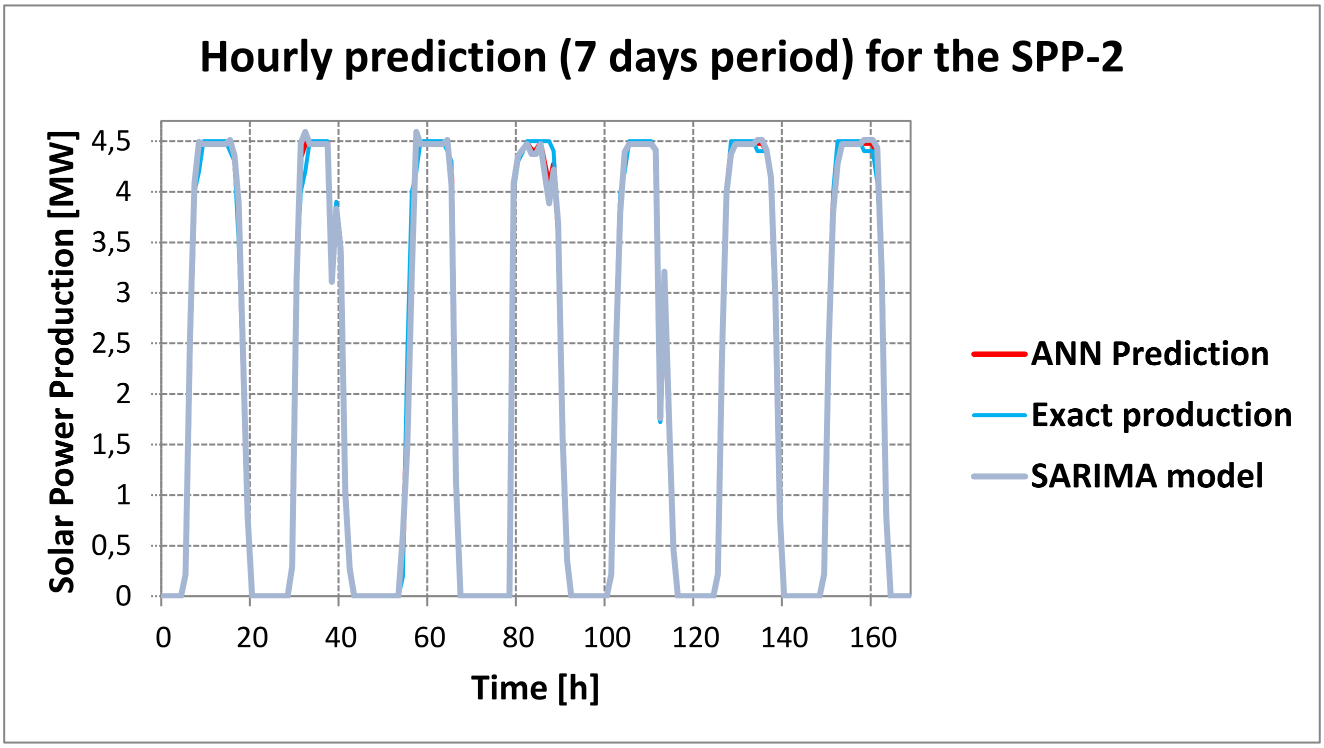

Fig. 11: Comparative analysis (7-days period) for SPP-2

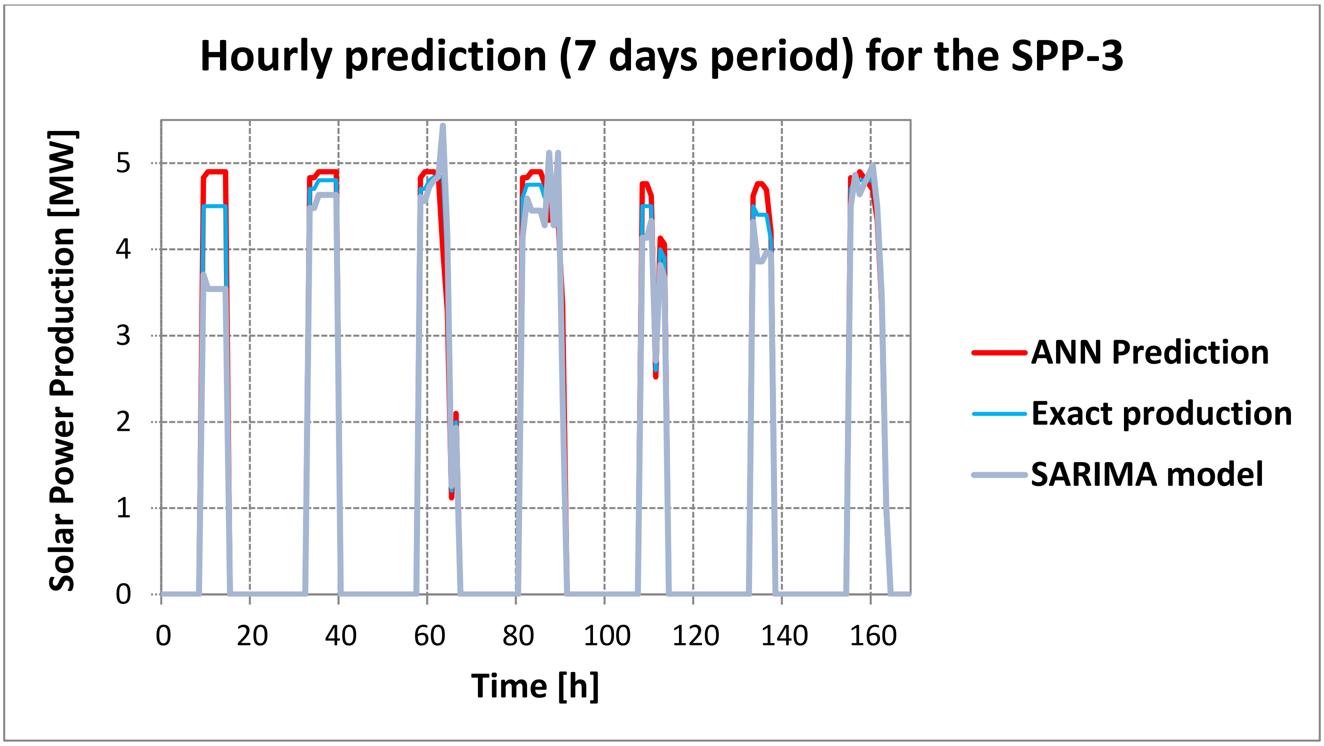

Fig. 12: Comparative analysis (7-days period) for SPP-3

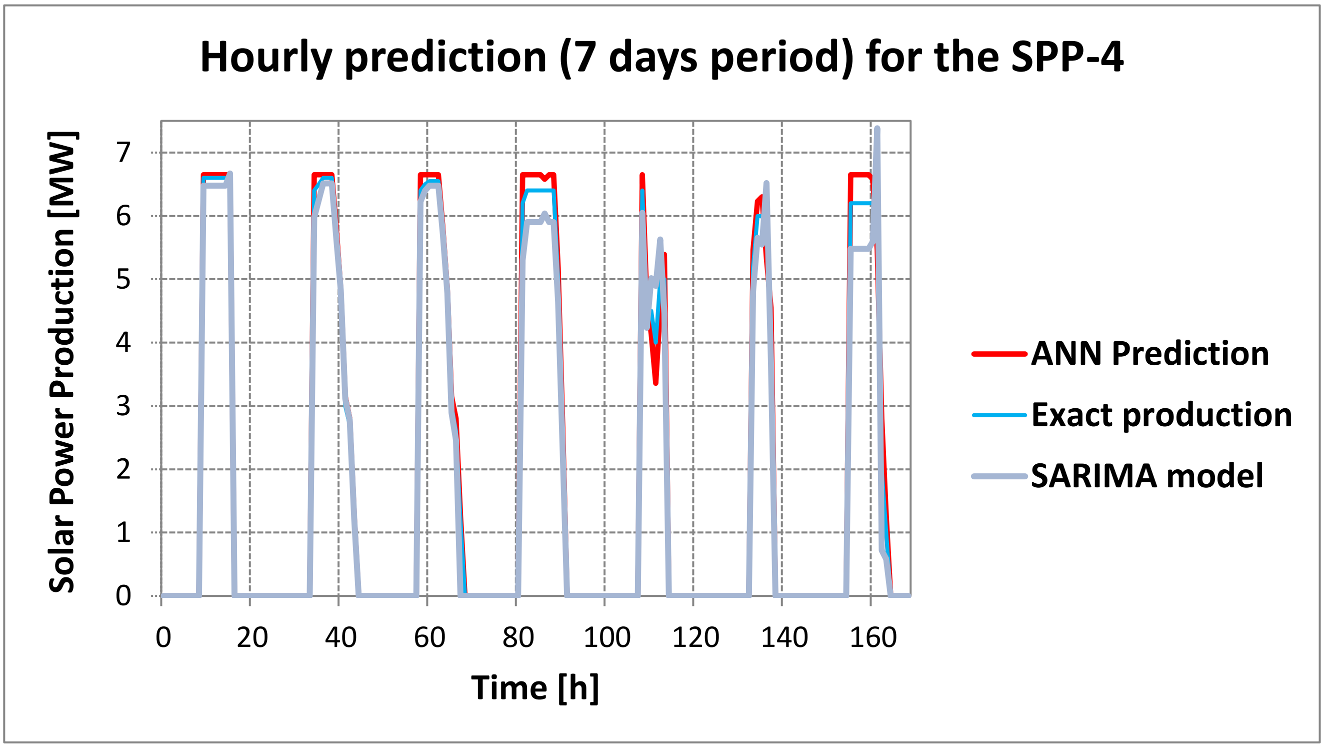

Fig. 13: Comparative analysis (7-days period) for SPP-4

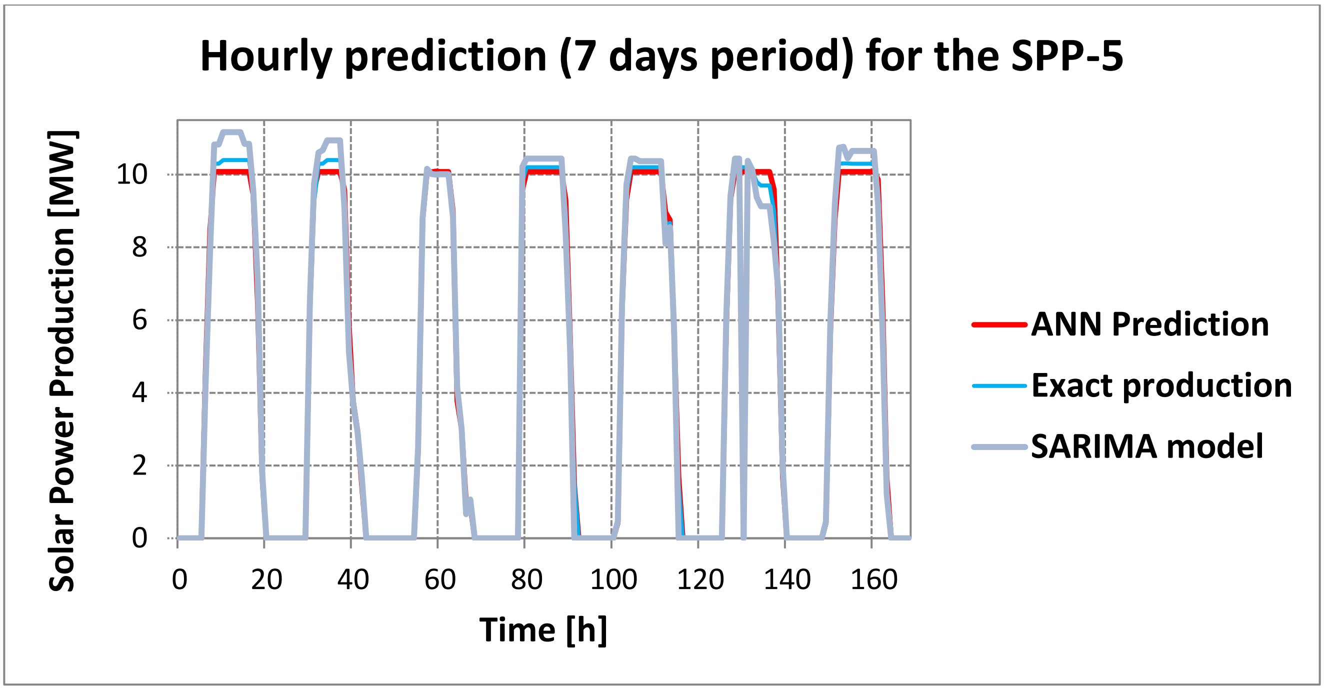

Fig. 14: Comparative analysis (7-days period) for SPP-5

As can be seen from Figure 10, Figure 11, Figure 12, Figure 13 and Figure 14, the forecasted values follow the exact measured production power well even for the SPPs. From the above presented diagrams, it is confirmed that the ANN forecasting method can be used efficiently and reliably for both main types of renewable energy sources. In Table 3 the average MAPE for SPP-1 to SPP-5 for the ANN forecast and the SARIMA model was approximately 1.4%-2.3% and 2.3% - 4%, respectively. MAPE of the SPP forecast using GA, [56], or DL, [57], is typically between 5% and 10%, highlighting the improvement made by the usage of the ANN methods.

It can be seen from the findings shown in that there is not much of a difference between the ARIMA model and the ANN model's predicting accuracy level. Based on the very modest forecast errors of both models, one could claim that they both performed well in terms of forecasting. Nonetheless, the ANN model consistently outperforms the ARIMA model in terms of forecasting accuracy using the test data. Nevertheless, ANN is superior. As a result, this research project also contributes to the clarification of views expressed in the literature about the advantages of the ANN model over the ARIMA model for time series prediction, [55].

From the aspect of energy balancing and long-term plans, ANN gives very good results. ANN can better and more accurately monitor changes in production and therefore generate a more realistic production plan for SPP and WP than classic planning methodologies.

4 Conclusions

The main goal of this work is to recommend and evaluate a new production forecasting technique for wind and solar power plants. It is trying to deal with the challenges of balance management that System Operators (SOs) face in the era of renewable energy sources. The paper presents a technique for forecasting wind and solar production that presents extremely high variability, creating problems for the distribution and transmission systems, which can lead the system out of its stable operation. The technique was based on ANN, and the forecast provided for wind and photovoltaic production was extremely accurate, proving that it is better than other forecasting techniques. Calculating the MAPE for the wind power plants and for the proposed ANN, it was found between 3% and 4.3%, when usually the current prediction methods have a MAPE of 5%–10%. Doing the same for solar power plants, it was also found that for the proposed ANN, the MAPE was between 1.4% and 2.3%, when usually the current prediction methods have a MAPE of around 9%. Also, the ANN forecast was almost the same regardless of the size of the installed wind or solar generation capacity. This fact, combined with the cooperation between the operators, will help to deal with the failures in the forecasting of production from renewable energy sources and the reliable and stable operation of the Greek Power System.

In this work, there was also a comparison between the proposed ANN and the SARIMA model. From their comparison, the proposed ANN is better than the SARIMA model since the MAPE for the SARIMA is approximately twice as high as the MAPE of the ANN. This proves that the proposed ANN is more efficient than the other prediction model (SARIMA). Also, SARIMA although is less efficient than the proposed ANN, is more efficient compared to the current prediction methods. This is something that needs further examination and perhaps a future hybrid method combining ANNs and the SARIMA method probably will show even better remarks.

The SOs, the MOs, and the flexible resources must work together effectively. Future research should combine the implementation of the proposed methodology with energy storage. Since the RES production prediction will be accurate enough, the energy storage will be held in an optimal way, depending on the power system's needs. Also, for the better accuracy of the proposed method, more data is needed, and at this time, this is limited. However, real-time data in the future can be collected using the Internet of Things, which will be available in the Greek TSO and DSO.

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List of Abbreviations

aFRR	Automatic Frequency Restoration Reserve
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
DL	Deep Learning
DSO	Distribution System Operator
GBT	Gradient Boosting Tree
KELM	Kernel Extreme Learning
MAPE	Mean Average Prediction Error
mFRR	Manual Frequency Restoration Reserve
ML	Machine Learning
PDF	Probability Density Function
RES	Renewable Energy Sources
RSS	Residual Sum of Squares
SCADA	Supervisory Control And Data Acquisition
SO	System Operator
SPP	Solar Power Plant
SVM	Support Vector Machine
TSO	Transmission System Operator
WPP	Wind Power Plant

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