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RESEARCH ARTICLE

Prediction of Power Generation of a Photovoltaic Power Plant Based on Neural Networks

RALUCA NELEGA[1], DAN IOAN GREU[1], EUSEBIU JECAN[1], VASILE REDNIC[2], CIPRIAN ZAMFIRESCU[3], EMANUEL PUSCHITA[1,2], (Member, IEEE), AND ROMULUS VALERIU FLAVIU TURCU[2,4]

[1]Communications Department, Technical University of Cluj-Napoca, 400027 Cluj-Napoca, Romania
[2]National Institute for Research and Development of Isotopic and Molecular Technologies, 400293 Cluj-Napoca, Romania
[3]Department of Telecommunications, Politehnica University of Bucharest, 061071 Bucharest, Romania
[4]Faculty of Physics, Babes-Bolyai University, 400084 Cluj-Napoca, Romania

Corresponding author: Romulus Valeriu Flaviu Turcu (Flaviu.Turcu@itim-cj.ro)

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ABSTRACT Photovoltaic energy production is an important factor for increasing the electricity supply. The ability to predict the electric power production (EPP) of a photovoltaic (PV) farm supports from the management process of the power grid to the trade in the energy market and much more. Also, by predicting the production of PV power (PVP), it is possible to monitor the lifetime of the solar cells that form the backbone of any solar PV system. As a critical result, sudden failures of the PV plant can be avoided. Using a long short-term memory recurrent neural network (LSTM-RNN) model, this work evaluates the prediction accuracy of two forecasting strategies: the recursive strategy and the non-recursive Multiple-Input and Multiple-Output, respectively. The dataset consists of 5-years in-filed production data measurements collected from the CETATEA photovoltaic power plant, a research site facility for renewable energies located in Cluj-Napoca, Romania. The high granularity of the electric power production dataset values recorded each 1 hour guarantees the overall prediction accuracy of the system. The impact of the dataset size, the number of previous observations, and the forecast horizon on the neural network prediction accuracy is evaluated for each strategy. The performance metrics used to evaluate the prediction accuracy are the root mean square error, the mean bias error, and the mean average error. The results analysis demonstrates the ability of the implemented machine learning models to predict electric power production, as well as their importance in the energy loss management process.

INDEX TERMS Power generation prediction, prediction accuracy, forecasting horizon, PV farm, solar energy.

I. INTRODUCTION

Industrialization and globalization determined an increase in energy consumption worldwide, as fossil fuels represented 80% of the world's energy use in 2019 [1]. What started as an unavoidable form of development became one of the biggest threats modern societies has ever faced: energy crisis, environmental pollution, and global warming, to mention a few well-known effects of energy overconsumption.

Renewable energy resources come as a sustainable alternative solution to this problem, with solar energy being considered one of the most promising alternatives to fossil fuels [2], [3]. The main advantage of solar power is its potential, knowing that, if captured, it would represent 5000 times more than the current world energy need [4].

The most used technology for converting solar energy into electric power is the photovoltaic (PV) cell. This technology

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is integrated in the national utility power grid through solar grids. Solar grid integration requires smart grids: intelligent systems aimed to prevent a potential outage of power over the grid [5]. Unfortunately, the intermittent nature of PV energy production has a great impact on the system's performance.

Therefore, accurate PV power forecasting represents a key element of the energy management systems, improving its reliability and maintaining the power required parameters [2], [6]. PV power generation is directly influenced by the weather conditions, i.e., temperature, humidity, and clouds movement, thereby making the prediction accuracy much more complex.

Artificial intelligence (AI) is a common approach for PV power forecasting [2], therefore it is used also in the current study.

The aim of this work is to predict the generation of PVP of a PV power plant using a neural network (NN) model and to analyze its performance on different forecasting horizons.

This work proposes hereby a long short-term memory recurrent neural network (LSTM-RNN) model that predicts the PVP output. LSTM can capture both, short-time and long-time dependencies in data, making it suitable for the purpose of this work. Its performance on different prediction horizons is analyzed using two forecasting strategies, recursive and Multiple-Input and Multiple-Output (MIMO). These strategies are evaluated with respect to three characteristics: root mean square error (RMSE), mean absolute error (MAE), and mean biased error (MBE).

As a software component, the test environment Google Colab was chosen to write, edit, and execute the models. Colab has integrated Python 3 modules used in building our models. Some examples of used modules are Pandas, Keras, Numpy, and Sklearn [7]. Python is a powerful tool used for its capabilities to work with machine learning models, incorporating advanced NN [8].

The originality of this work consists in the processing of real data collected from a PV power plant located in Cluj-Napoca, Romania. The PV consists of 102 PV solar panels. The data used in the prediction process are collected over 6-year time span, from 2016 to 2022. The number of samples used in our dataset is 43824, each sample representing the power generated in an hour.

The contributions of this work are summarized, but not limited to, as follows:

1) Firstly, the proposed strategies (recursive and MIMO) used by our models provide versatility for a forecaster to choose the best model based on his case scenario.
2) Secondly, analysis of the methods regression using the window technique and regression with time-steps allows the decision to select the best recursive model to compare with MIMO one.
3) Finally, this work evaluates the impact of the amount of data used as on the prediction accuracy.

The present study is organized in six sections. Section II presents the state-of-art regarding prediction methods for power generation. The solar panels and the PV power plant is described in Section III. Section IV presents the neural network processing algorithms and the proposed analyzing approach, while Section V outlines the prediction results. Finally, Section VI concludes the work.

II. LITERATURE REVIEW

PV power forecasting is a topic widely investigated due to its economic and ecologic impact [2], [9], [10], [11], [12], [13], [14], [15], [16], [17]. Research by Wan et. al. [2] provides a review and comparison of the most used methodologies for PV power prediction: statistical approach, artificial intelligence (AI) approach, physical approach, and hybrid approach. Another classification of PV power forecasting is realized by Antonanzas et. al. in [15], according to the prediction horizon: intra-hour (less than 1h), intra-day forecast (1h-6h), six hours to-day ahead (6h-48h) and two days ahead or longer forecasts. Each category has its own applications, intra-day forecasts having for example load-following purposes, while two days ahead or longer predictions playing an important role in transmission management, trading, hedging, planning and asset optimization.

The proposed model performs multistep ahead forecasts, using a LSTM neural network and analyzes different prediction horizons, covering several categories from intra-day to two days ahead forecasts. Because prediction of the PV power plant energy production can be seen as a time-series forecasting problem, the chosen network is an extension of Recurrent NN (RNN).

RNN is the most commonly used neural network architecture for this kind of assessments, having a feedback connection that stores information about recent input events in the form of short-term memory [18]. Even if classical RNNs perform satisfactorily in the case of short-term time dependencies, in the case of long-term time dependencies they have poor performance due to the vanishing gradient problem [18], [19]. A solution for this limitation is the Long Short-Term Memory (LSTM) Network proposed in [19].

LSTM represents an extended version of RNN that is able to learn short-term as well as long-term time dependencies, this characteristic making it suitable for our task. Moreover, the decision of using the LSTM neural network in our work is supported by the results obtained in [9], [10], [11], and [12], where the PV power is predicted also using this neural network, proving its performance in the PV forecasting problem.

Similar to [20] and [21], two strategies characteristic of multistep ahead time series forecasting problems are examined using the LSTM network, namely the recursive strategy and Multiple-Input and Multiple-Output (MIMO) strategy, respectively. Our analysis offers a clear vision of the differences between the strategies mentioned before, concluding that MIMO strategy performs better than the recursive one, the forecast horizon being increased.

The recursive strategy is based on a model that performs a one step ahead forecast, meaning that the performance of the model on any prediction horizon is strongly dependent by its performance in the case of one step ahead prediction.

Therefore, the optimization of the model is performed taking into consideration a one step ahead forecasting model.

It is essential to state that compared to [9], [11], and [12], our approach uses the grid search algorithm for hyperparameter optimization.

Moreover, the dataset used, spanning over 5 years of observations is more significant than the data sets used by Abdel-Nasser et. al. [9] and Harrou et. al. [12], that train and test the model on data collected in a single year, respectively Akhter et. al. [11] uses four years of data.

Similar to [9], our approach compares two different architectures of the one step ahead prediction model: regression using window technique and regression using time-steps, the evaluation metric used to choose the best configuration being RMSE. The conclusion is that the regression using time-steps has better performance than the one using window technique.

MIMO strategy presents a model that aims to predict a large number of values at once, which defines a time sequence of the predicted values. This approach is well illustrated in other articles such as [21], [22], and [23]. Therefore, the grid search technique is also used to optimize the hyperparameters of the model.

This optimization method for the MIMO strategy is also used in [22] to determine the number of neurons in each layer, the number of samples used as input, the batch size, and the number of epochs. Moreover, the data set used is composed of samples at a 15-minute interval, collected over a month, in comparison with our dataset that is composed of samples at a 1-hour interval, collected over 5 years. In this work, a model performs well if the RMSE value is as small as possible, this approach being frequently found in the literature [21], [22], [23], [24], [25], [26].

Studying a different approach [27], hyperparameters of the studied model are optimized using Tree-Structured Parzen Estimator (TPE), an iterative process that uses a history of evaluated parameters to create models, which are used to suggest the next set of parameters to evaluate. Compared to this, our MIMO model uses the grid search method to determine the best combination of hyperparameters, evaluating all the combinations of the hyperparameters and goes for the best one. In the case of MIMO strategy, the results are not influenced by the accumulation of errors as in the case of the recursive strategy. Our work presents the methods to obtain the best results of RMSE values for each strategy.

III. CENTER FOR RESEARCH AND ADVANCED TECHNOLOGIES FOR ALTERNATIVE ENERGY (CETATEA) PHOTOVOLTAIC POWER PLANT

The Center for Research and Advanced Technologies for Alternative Energy (CETATEA) resulted as a response to the transition need to renewable energy. It was created, within the National Institute for Research and Development of Isotopic and Molecular Technologies (INCDTIM) form Cluj-Napoca, Romania, based on a project co-financed by the European Regional Development Fund, and it was completed in November 2015 [28].

The main research topics in CETATEA are related to development of techniques and capabilities to harvest, convert, and store the alternative produced energy (solar, wind, hydroelectric power). Furthermore, the Center is equipped with a 25 kW PV farm.

Figure 1 illustrates CETATEA building and the PV farm.

FIGURE 1. CETATEA research center at INCDTIM Cluj-Napoca, Romania.

The energy produced by the PV system is converted by a SMA Sunny Tripower 25,000 TL-30 inverter and transferred to be consumed locally. The excess of energy is either stored in a Vanadium redox flow battery FB 10–40 or transferred to the national power grid. The PV farm consists of 102 solar panels arranged in 17 rows, with 60 cells per panel, making a total of 6120 cells. The PV panels are connected according to the wiring diagram presented in Figure 2.

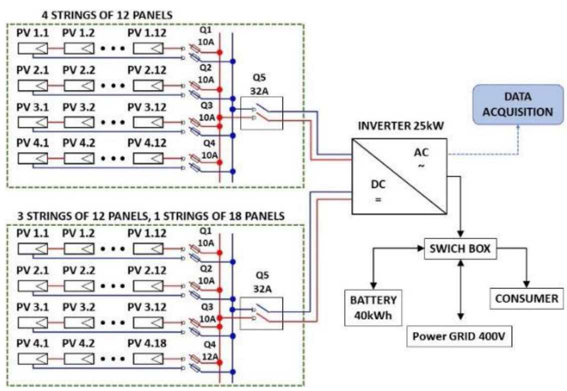

FIGURE 2. Electric schematic of CETATEA Research Center PV system.

The PV panels are polycrystalline type, JC245M-24/Bb model, produced by ReneSola Jiangsu Ltd. company [29].

Their main characteristics are presented in Table 1.

The data analyzed in this study were collected directly from inverter via Sunny Portal online platform [30].

Over the time, the panels elements can break one by one. The impact is felt over long intervals, directly into the power generation.

TABLE 1. Units for magnetic properties.

Parameter	Value
Maximum Power (Pmax)	245 W
Power Tolerance	0/+5W
Open Circuit Voltage (Voc)	37.3 V
Short Circuit Current (Isc)	8.73 A
Maximum Power Voltage (Vmp)	29.9 V
Maximum Power Current (Imp)	8.19 A
Maximum System Voltage	1,000 VDC
Maximum Series Fuse Rating	20 A
Dimension (LxWxH)	1,640x992x40 mm
Weight	19 kg

Inspections of PV plants performed with thermal vision drones is one of the most efficient the solution. It is reliable, precise using state of the art equipment for the best quality data, and it can produce automatic reports with pinpointed anomalies and certain numbers for comparisons. Drone inspection is about 10 times more efficient and needs 90% less inspection time than traditional methods.

To confirm if there is any power production drop of the PV pharm considered in our study, a thermal inspection of the panels was performed.

During the solar inspection, we utilized an industrial-grade drone fitted with a specialized thermal camera capable of producing high-resolution thermal images. The drone used was the DJI M300 RTK, equipped with a Zenmuse H20N sensor, which has a 640 × 512 pixel image resolution for thermal imaging.

The temperature range captured by the camera is -20°C to 150°C (High Gain) and 0°C to 500°C (Low Gain), with a spectral band of 8-14μm and a sensitivity (NETD) of $\leq$50 mK at aperture f/1.0.

A comparison between RGB image and thermal view of the PV farm is presented in Figure 3.

The thermal inspection revealed 3 panels with faulty cells due to solar anomalies and a total of 8 faulty cells were detected. This indicates that 99.87% of the park is functioning properly.

The inspection shows that power generation is efficient, and the produced power is close to the estimated output.

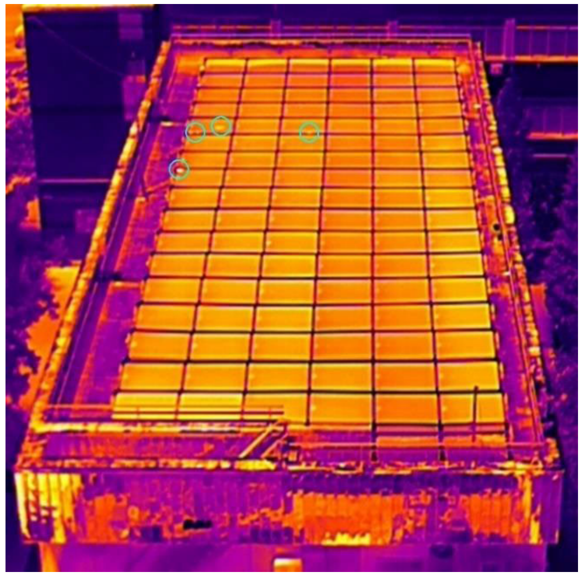

FIGURE 3. Thermal scanning using drone inspection displays the hot sport on the PV farm using an industrial-grade drone: 8 faulty cells in 3 PV panels.

IV. MACHINE LEARNIG/NEURAL NETWORK PROCESSING ALGORITHMS

Due to the increasing availability of data in recent years, artificial neural networks (ANNs) have become popular for many ML tasks [18]. Various studies highlighting the advantages of using ANNs in prediction problems are also presented [31]. Being universal approximators, ANNs can model any relationship in the data and generalize them to unseen data, covering a much higher range of functions than the classical statistical techniques [18].

A. LONG SHORT-TERM MEMORY NETWORK (LSTM)

LSTM is a type of RNN that is able to learn both short-term and long-term time dependencies. Unlike the classical ANNs that are composed of neurons, the LSTM network consists of memory blocks with components (gates) that control the state of the block and the output. The structure of a LSTM unit is shown in Figure 4.

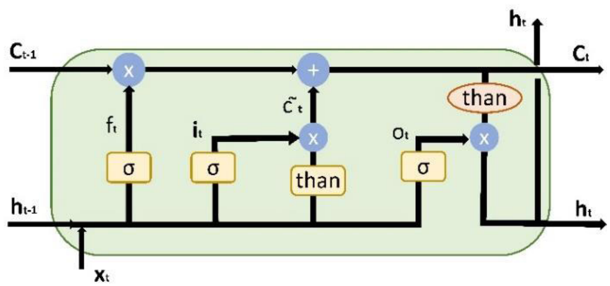

FIGURE 4. LSTM unit.

There are three types of gates in the LSTM block which control the cell state c_t at the time t: forget gate f_t, input gate i_t, and output gate o_t. The LSTM unit receives at each time step inputs from two external sources, namely the current sample x_t and the hidden state of the previous sample h_{t-1}.

Each gate has an internal source, also, the cell state at the previous time step c_{t-1}.

The mathematical relationship between inputs and outputs is expressed as follows:

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{1}$$

$$c_t = f_t c_{t-1} + i_t \tilde{c}_t \tag{2}$$

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right) \tag{3}$$

$$\tilde{c}_t = tanh\left(W_c\left[h_{t-1}, x_t\right] + b_c\right) \tag{4}$$

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \tag{5}$$

$$h_t = o_t tanh\left(c_t\right) \tag{6}$$

where W_f, W_i, W_o, W_c represent weight parameters, b_f, b_i, b_o, b_c are bias parameters, x stands for the input and h for the output. The recurrent activation function is denoted by σ, representing the sigmoid function and the activation function is the hyperbolic tangent function.

The forget gate decides what information to keep and what information to erase from the cell state based on the value outputted by the recurrent activation function. The sigmoid function takes values between 0 and 1, where 0 means "completely keep" and 1 means "completely forget". In equation (3) is expressed the input gate that sets the input values to be updated, quantifying the importance of the new information.

In the same way, the output gate decides which part of the cell state to be exposed as output. The activation function *tanh* scales the value of the candidate memory cell $\tilde{c}_t$ (4) and the value of the hidden state element h_t (6) between [-1,1]. The operation of the gates is controlled by the values of the weights and biases, values adjusted by an optimization algorithm [9], [19].

B. EVALUATION INDICES

There are a number of indicators which evaluate the forecasting performance of a model.

The most common indices are mean bias error (MBE), mean absolute error (MAE), and root mean square error (RMSE), expressed in the following equations [2].

$$MBE = \frac{1}{N}\sum_{i=1}^{N}[\hat{x}_i - x_i] \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{x}_i - x_i| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{x}_i - x_i)^2} \tag{9}$$

where $\hat{x}_i$ represents the i^{th} prediction, x_i is the i^{th} observation and N denotes the size of the test dataset.

Each metric provides different information about the accuracy of the model. MBE indicates if the model over or underestimates, while RMSE penalizes large errors. On the other hand, MAE is used for evaluating uniform errors, showing the average distance between the real and predicted values [15].

In our study, the RMSE is employed in the optimization process, when the best configuration of each strategy is considered to be the one with the lowest RMSE.

In the final step, in order to validate the performance of the chosen configurations, each of them is evaluated in terms of: RMSE, MAE, and MBE on a different dataset than the one used in the optimization process.

C. PROPOSED APPROACH

The aim of this study is to forecast the production of energy of a PV power plant using the LSTM network. Being reduced to a multi-step ahead time series forecasting problem, it can be approached in various ways.

Ben Taieb et al. [21] have identified 5 different strategies for this task: recursive strategy, direct strategy, DirRec strategy, MIMO strategy, and DIRMO strategy. The direct, DirRec and DIRMOstrategies imply multiple models to be trained, these approaches being time consuming.

Therefore, in this work we analyze the recursive strategy and the MIMO in order to compare their performance on a specific dataset.

1) RECURSIVE STRATEGY

The recursive strategy is the most intuitive forecasting strategy. A model trained to perform a one-step ahead forecast predicts the entire horizon, using previously predicted values as part of the input to estimate the next value [21].

The forecasts are indicated in equation (10):

$$\hat{y}_{N+i} = \begin{cases} M\left(y_{t-N+1}, \ldots, y_t\right), \; if \; i = 1 \\ M\left(y_{t-N+i}, \ldots, y_t, \hat{y}_{t+1}, \ldots, \hat{y}_{t+i-1}\right) \\ \qquad\qquad if \; 2 \le i \le N \\ M(\hat{y}_{t+i-N}, \ldots, \hat{y}_{t+i-1}) \; if \; i > N \end{cases} \tag{10}$$

where y_i is the observed value at the time i, $\hat{y}_i$ represents the predicted value at the time i, N is the number of the past values of the time series and M is the trained model.

Figure 5 illustrates the principle of the recursive strategy.

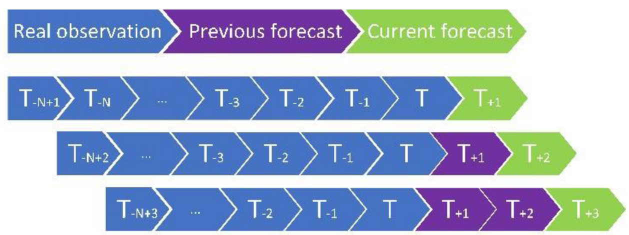

FIGURE 5. Recursive multi-step prediction.

Because the predicted values are used for forecasting the next steps, the strategy is susceptible to the accumulation of errors with the increase of the prediction horizon [21]. As a result, the performance of the model for the multi-step prediction is directly affected by its accuracy in the case of the one-step ahead forecast.

Abdel-Nasser and Mahmoud [9] have shown that two LSTM architectures are efficient for PV power forecasting, namely, LSTM for regression using the window technique, respectively the time steps.

Both use PVprior times (t, t-1, t-2, ...) to predict the PV power at the next time (t+1), performing a one-step ahead prediction. In the case of the window technique, the previous observations are used as separate input features, whereas in the second approach they are used as time steps of one input feature.

Both architectures are analyzed and the best one is used to perform multi-step ahead predictions by applying the recursive strategy detailed above.

2) MIMO STRATEGY (NON-RECURSIVE STRATEGY)

MIMO strategy stands for multiple input, multiple output and is also known as many-to-many relationship.

The non-recursive strategy's primary goal is to use a sequence of data to predict next H values, using previous N values [21].

Prediction of the model is indicated in the following equation:

$$\begin{gathered} M\left(\left[X_1, \ldots, X_N\right]\right) =>\left[Y_{N+1}, \ldots, Y_{N+H}\right], n=0 \\ M\left(\left[X_{1+H}, \ldots, X_{N+H}\right]\right) =>\left[Y_{N+H+1}, \ldots, Y_{N+2H}\right] n=1 \\ M\left(\left[X_{1+nH}, \ldots, X_{N+nH}\right]\right) =>\left[Y_{N+nH+1}, \ldots, Y_{N+(n+1)H}\right] \\ n \geq 2 \end{gathered} \tag{11}$$

where M is the trained model, $[X_{1+nH}, \ldots, X_{N+nH}]$ is the real data sequence, $\left[Y_{N+nH+1}, \ldots, Y_{N+(n+1)H}\right]$ is the predicted sequence while n is the number of times predicted. Figure 6 illustrates the principle of the non-recursive strategy.

FIGURE 6. Vector output prediction.

3) PROPOSED MODEL

Both recursive and non-recursive strategies use a 3 layers LSTM networks as illustrated in Figure 7.

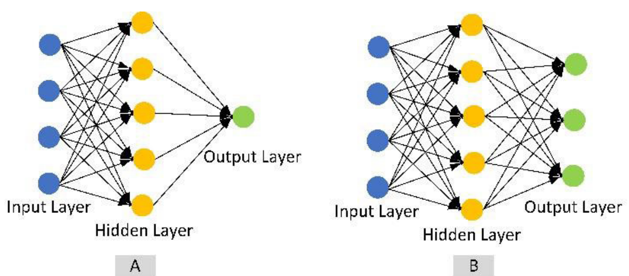

FIGURE 7. LSTM network: recursive strategy (A) and MIMO strategy (B).

Each layer contains several nodes, their number influencing the performance of the model. The number of nodes in the input layer represents the number of time steps taken into consideration when making a prediction and the number of nodes in the output layer equals the number of predicted values.

Therefore, as presented in Figure 7, this is the only difference between the two strategies used in our study: the recursive strategy uses only one node in the output layer (A), predicting a single value, while the non-recursive strategy requires multiple nodes in this last layer (B).

The hidden layer is formed of LSTM units, the number of nodes in this layer representing a hyperparameter that has to be optimized. Hyperparameters are parameters of the model that are set prior to the learning process and affect its performance.

The learning process is iterative, each iteration updating the weights and the biases of the model. The model is updated using an optimization algorithm which calculates the error between the predicted values and the expected ones based on the loss function, adjusting the internal parameters to minimize this error.

Hyperparameters such as number of epochs and batch size directly affects this process. The number of epochs represents how many times the entire dataset is passed completely through the neural network and the batch size is the number of processed samples before the internal parameters are updated.

There is no clear relationship between the values of the hyperparameters and the accuracy of the model [32], therefore a proper combination must be identified for each case.

The hyperparameter optimization is performed with the grid search algorithm [33], that trains a model for every combination of hyperparameters and evaluates its accuracy according to a predefined metric, as indicated in [32].

The chosen metric is RMSE and the tuned hyperparameters are the number of nodes of the hidden layer, the number of epochs, batch size and the number of previous observations used as input (number of nodes in the input layer).

Given the high computation time of the grid search technique, other hyperparameters such as loss function (i.e., mean square error) and optimizer (Adam) are selected as in [9] and [10].

4) PROPOSED ANALYSIS METHOD

To compare the two forecasting strategies, each strategy is analyzed separately, evaluating both their performance on different forecasting horizons and the impact of the amount of data used for training and the impact of the number of previous observations used as input for the prediction accuracy.

The dataset is divided into three subsets, namely training set, validation set, and test set. The validation dataset is used in the hyperparameter optimization step, the best model being considered the one that has the smallest RMSE on this set of data.

In order to provide an unbiased evaluation of the chosen final model, its performance is evaluated finally on the test dataset, this time considering 3 different evaluation metrics: RMSE, MAE, and MBE.

The main steps of the proposed analysis method are presented in Figure 8.

V. PREDICTION OF ENERGY PRODUCTION

A. DATA COLLECTION AND DATA PREPROCESSING

The study is based on data collected from 16 April 2016 to 15 April 2022 every 15-minutes from a PV power plant. Because the dataset is not complete, the discontinuities are filled replacing the missing values with the power produced at the same hour in the previous day.

As illustrated in Figure 9, there is a longer period of time in 2019 when the PV power generated by the solar panels was not recorded, therefore one year is removed from the dataset.

To preserve the seasonality of data, the gap in the dataset corresponds to exactly 365 days (28^{th} October 2018-27^{th} October 2019), so that the analysis is not by affected by

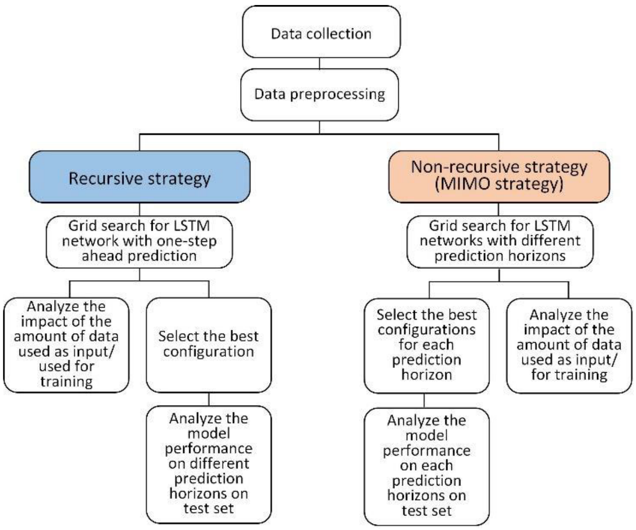

FIGURE 8. Prediction Block scheme of the proposed analysis method.

uneven distribution of data. In this manner, 5 continuous years of data from every 15-minutes can be simulated.

The model used in this study operates with the PV power produced every hour. Consequently, the power generated in an hour is calculated as the mean of 4 samples from every 15-minutes.

The hourly distribution of the PV power generated in the 5 years is illustrated in Figure 9.

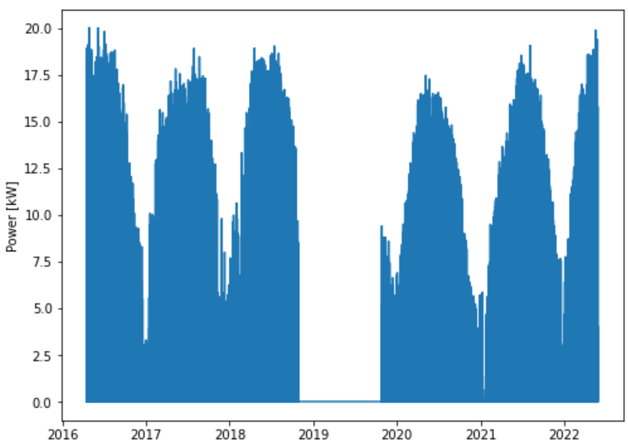

FIGURE 9. Five years (2016-2022) of energy production with a one-year gap.

B. RECURSIVE STRATEGY

From here on, both architectures are evaluated on validation dataset in terms of RMSE, using different amounts of data for training and a forecast horizon of one hour. The scenario that gives the best results is selected to analyze the impact of the forecast horizon on the prediction accuracy.

1) IMPACT OF DATASET SIZE

To study the impact of the amount of data used for training on the prediction accuracy, two different time-intervals are proposed for model training: data from a single year (16 April 2019 to 15 April 2020), and data from three years (16 April 2016 to 15 April 2020). The model is validated in both cases on data recorded in the interval 16 April 2020 to 15 April 2021 (i.e., one year). A grid search is performed in each case for both architectures with a search space defined in Table 2.

TABLE 2. Hyperparameter search space.

Hyperparameter	Search Space
Number of input previous observations	24, 36, 48, 60, 72
Number of nodes	50, 100, 200
Number of epochs	10, 50, 100
Batch size	32, 64, 100, 200

Table 3 presents the best configuration of hyperparameters for each scenario.

TABLE 3. Best configuration of hyperparameters for each scenario.

Model architecture	No. of years for training	Scenario	RMSE	No. of previous observations used as input	No. of nodes	No. of epochs	Batch size
Window technique	1	I	1.084	24	200	10	32
	3	II	1.044	24	200	50	200
Time steps	1	III	1.034	48	50	50	64
	3	IV	1.019	48	50	50	64

Training both architectures with bigger dataset results in the decrease of the RMSE. The result analysis indicate that the accuracy of the models is improved using more collected data.

The best configuration proved to be obtained in scenario IV, where the architecture is the LSTM for regression with time steps and the training dataset is composed of data collected over a period 3 year.

2) IMPACT OF THE NUMBER OF PREVIOUS OBSERVATIONS USED AS INPUT ON THE PREDICTION ACCURACY

The results analysis indicate that the proposed architectures are differently affected by the number of samples used as input.

Table 4 presents the first 10 ordered RMSE values obtained after applying the grid search algorithm for each scenario and the corresponding number of previous observations used as input.

If in the case of the window technique the best results are obtained when the number of samples used as input is smaller (i.e., 24, 36), for the second architecture (regression using time steps) it results that the accuracy of the model is not influenced by the number of previous observations used as input, as presented in Table 4.

Because the smallest RMSE is obtained in a configuration that uses 48 samples as input data, this number of samples will be used also when analyzing the recursive strategy on different forecast horizons.

TABLE 4. Ordered RMSE values after grid search and the corresponding number of inputs.

Scenario	RMSE [kW]	No. of previous observations used as input	Scenario	RMSE [kW]	No. of previous observations used as input
I	1.0845	24	III	1.0344	48
	1.0886	24		1.0352	48
	1.0888	36		1.0381	24
	1.0962	24		1.0394	72
	1.0978	24		1.0415	24
	1.1033	60		1.0436	24
	1.1036	36		1.0436	72
	1.1119	24		1.0458	24
	1.1165	48		1.0468	60
	1.1179	72		1.0495	72
II	1.0446	24	IV	1.0195	48
	1.0566	24		1.0249	24
	1.0598	36		1.0270	24
	1.0619	36		1.0272	48
	1.0645	24		1.0278	48
	1.0662	24		1.0283	36
	1.0665	24		1.0285	24
	1.0718	36		1.0295	72
	1.0719	24		1.0297	24
	1.0752	24		1.0310	72

3) IMPACT OF THE FORECASTING HORIZON ON PREDICTION ACCURACY

The best configuration obtained in scenario V estimates the PVP produced in the next hour based on observations from the last 48 hours.

To study the impact of the forecasting horizon on prediction accuracy, the testing dataset is divided into sets of lengths equal to the forecast horizon. The first value from each set is estimated using 48 real observations as input and the next predictions from the set are performed based on values estimated previously.

In this manner, the entire testing dataset is covered, as shown in Figure 10.

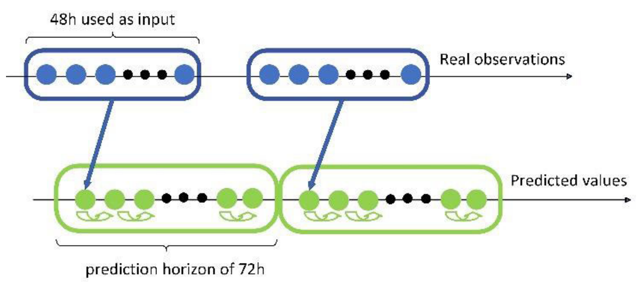

FIGURE 10. Multi-step recursive prediction of the entire year with a forecast horizon of 72 hours.

The dataset used for the test consists of 365 days (16.04.2021-15.04.2022). The accuracy of the model is improved by limiting the predicted power to 0, avoiding the case of negative values. The evaluation is made using three different evaluation metrics, namely RMSE, MAE and MBE, calculated after the entire testing dataset is predicted.

Table 5 presents the performance of the model considering different forecast horizons.

TABLE 5. RMSE, MAE and MBE corresponding to each forecasting horizon.

Forecasting horizon (hours)	RMSE [kW]	MAE [kW]	MBE [kW]
1	1.123	0.50	0.02
6	1.824	0.90	-0.25
12	2.337	1.21	-0.60
18	2.455	1.31	-0.56
24	2.711	1.48	-0.46
30	2.715	1.48	-0.54
36	2.784	1.53	-0.66
42	2.856	1.60	-0.62
48	2.935	1.66	-0.60
54	3.001	1.71	-0.72
60	3.209	1.84	-0.82
66	3.313	1.91	-0.90
72	3.258	1.87	-0.80

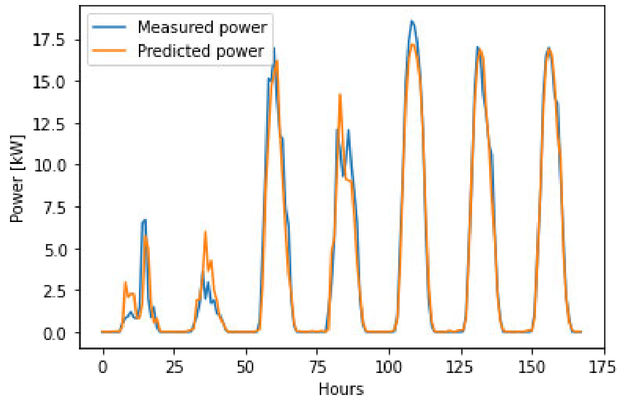

FIGURE 11. Measured power vs. predicted power corresponding to a forecasting horizon of 1h along 7 days (09 - 15 April 2022).

For smaller forecasting horizons, the RMSE, MBE and MAE increase significantly with the horizon, while for greater forecast horizons, the increasing trend is milder.

Moreover, except when the forecasting horizon is 1 hour, the negative values of MBE indicate that the model tends to underestimate the results.

Figures 11 and 12 illustrate the differences between the real data and the forecasted values over 7 days when the forecast horizon is 1 hour, respectively 24 hours.

Figure 12 shows that the prediction accuracy of the model is worsened with the increase of the forecasting horizon, thus proving the poor performance of the recursive forecasting strategy for longer term forecast.

C. MIMO STRATEGY

The non-recursive strategy implies a model that predicts a sequence of values using the previous sequence as input.

As a result, the performance of the model is directly affected by input sequences. As seen in the case of recursive strategy, the best LSTM architecture is regression based on the time steps, this architecture being used for analyzing the MIMO strategy.

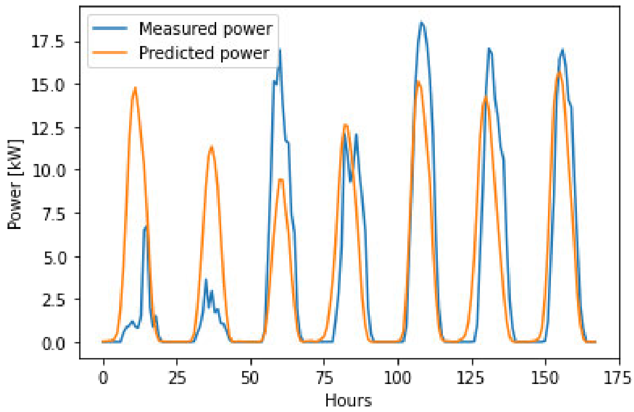

FIGURE 12. Measured power vs. predicted power corresponding to a forecasting horizon of 24h along 7 days (09 - 15 April 2022).

TABLE 6. Hyperparameter search space.

Hyperparameter	No. of values used
Input previous observations	24, 36, 48, 60, 72
Predicted values in a sequence	6,12,18,24,30,36,42,48,54,60,66,72
Nodes	50, 100, 200
Epochs	10, 50, 100
Batch size	32, 64, 100, 200

TABLE 7. Best configuration of hyperparameters.

No. of years used for training	Scenario	RMSE	No. of previous observations used as input/ No. of predicted values in a sequence	No. of nodes	No. of epochs	Batch size
1	V	1.8896	24/12	20	50	32
3	VI	2.1972	36/24	200	100	32

The selection process to determine the best scenario for the model based on the non-recursive strategy is illustrated in Figure 8.

1) IMPACT OF DATASET SIZE

To study the impact of the amount of data used for training on the prediction accuracy and to compare the results of strategies used, are proposed the same approaches as for the recursive strategy: model training with data from a single year (i.e., scenario V), and model training with data from three years (i.e., scenario VI). Also, the datasets used for training and testing the models are the same as in the previous studied strategy, namely the recursive one.

A grid search is performed, for the non-recursive strategy, with a search space defined in Table 6.

Table 7 presents the best configuration of hyperparameters.

Training the model with a bigger dataset result in the increase of the RMSE. This suggests that, unlike the recursive strategy, in the MIMO case the collection of more data will not improve the performance of the model. Also, the number of input variables is higher than the number of output variables, meaning that the size of the input sequence needs to be larger than the forecast horizon.

2) IMPACT OF THE NUMBER OF PREVIOUS OBSERVATIONS USED AS INPUT ON THE PREDICTION ACCURACY

Results analysis indicates that the performance of the model is decreasing by increasing the size of the sequence provided as input.

Table 8 presents the first 10 ordered RMSE values obtained after applying the grid search algorithm for each dataset used for the two scenarios.

TABLE 8. Ordered RMSE values after grid search and the corresponding number of inputs/outputs.

Scenario	RMSE [kW]	No. of previous observations used as input / predicted values in a sequence
V	1.889607	24 / 12
	1.896939	24 / 6
	1.899347	24 / 12
	1.899517	24 / 6
	1.900018	36 / 6
	1.900095	36 / 6
	1.90074	24 / 12
	1.903751	36 / 12
	1.904314	36 / 6
	1.904836	36 / 24
VI	2.197214	36 / 24
	2.202791	60 / 24
	2.203548	24 / 6
	2.238447	24 / 6
	2.24637	24 / 6
	2.246634	24 / 6
	2.252585	24 / 6
	2.255059	24 / 6
	2.257989	24 / 6
	2.260655	24 / 6

3) IMPACT OF THE FORECASTING HORIZON ON PREDICTION ACCURACY

Using the non-recursive strategy, the LSTM model estimates the PV power produced in the next hours based on past values.

Because the best results were obtained in scenario V, where the training dataset is composed of one year, the configurations obtained after the grid search process in this scenario are analyzed on the test dataset.

Table 6 illustrates the values of forecast horizon used for the model training process. Consequently, the best results of RMSE obtained after grid search for models are presented in in Table 7. The most advantageous forecast horizon consists of 12 samples using 24 samples as input.

In this manner, the representation of the testing dataset can be seen in Figure 13.

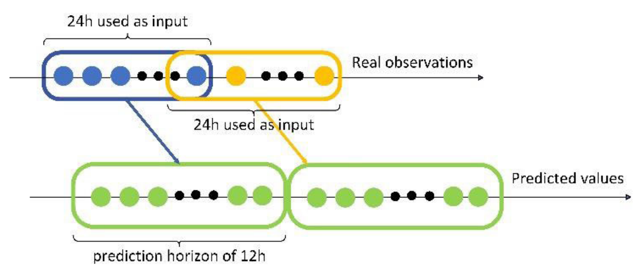

FIGURE 13. Multi-step non-recursive prediction of the entire year.

For a better view of the results, in Figure 14 is presented also graphically the performance of the configuration with

24 samples as input and 12 samples as output on the testing dataset. It can be observed that the values of the predicted PV power are close to the real ones, proving the advantage of using the MIMO strategy.

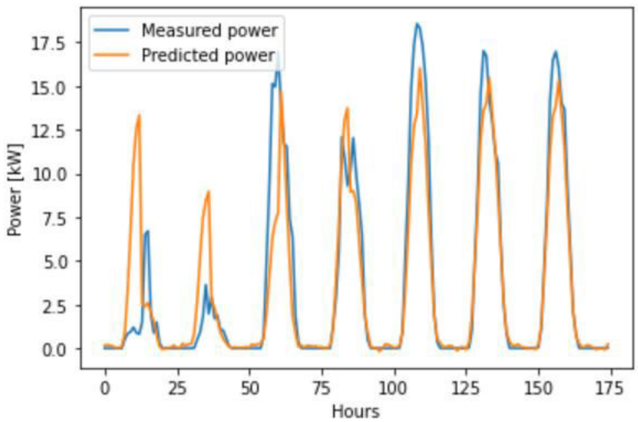

FIGURE 14. Measured power vs. predicted power corresponding to a forecasting horizon of 12h along 7 days (09 - 15 April 2022), using 24h as input.

In order to make a comparison between the MIMO and the recursive strategy, in Figure 15 is illustrated the performance of the MIMO strategy in a similar situation as the one presented in Figure 12.

The configuration used to analyze a forecast horizon of 24 hours is the one that had the smallest RMSE for this forecasting horizon after the grid search process.

As presented in Table 8, the configuration with 36 input samples and trained with one year of data gave the best results, thus it is used to compare the two strategies.

It can be observed that for the same forecast horizon and on the same testing dataset, the MIMO strategy gives better results than the recursive one.

The best configuration obtained after the grid search process for each forecast horizon was analyzed also for the testing dataset in terms of RMSE, MBE and MAE. The results obtained are presented in Table 9.

The RMSE value gets worse with the increase of the forecasting horizon. The MAE also has an increasing trend, even though the forecast horizon does not directly affect its value.

For example, the MAE obtained for a 30-hour horizon is higher than the values obtained for a 36-, 42-, or 48-hour horizon. In the case of MBE, no correlation between the prediction horizon and this metric can be established, the best value being obtained for the 66-hour horizon.

To see better the difference between the above-mentioned strategies, the results obtained in Table 5 are compared to the results from Table 9.

For the smallest forecasting horizon (horizon of 6 hours), the RMSE obtained with the recursive strategy is smaller than the results obtained with the MIMO one. On the other hand, for all the other forecasting horizons the MIMO strategy outperforms the recursive strategy not only in terms of RMSE, but also in terms of MAE and MBE. In both cases MBE has negative values, which means that overall, both strategies underestimate the results.

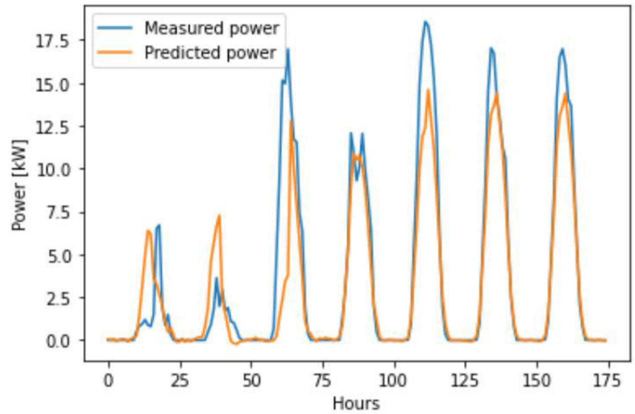

FIGURE 15. Measured power vs. predicted power corresponding to a forecasting horizon of 24h along 7 days (09 - 15 April 2022), using 36h as input.

TABLE 9. RMSE, MAE and MBE corresponding to each forecasting horizon With 24 values as inputs.

Forecasting horizon (hours)	RMSE (kW)	MAE (kW)	MBE (kW)
6	1.89	0.76	-0.16
12	1.88	0.75	-0.14
18	2.04	0.88	-0.23
24	2.08	0.93	-0.47
30	2.16	1.01	-0.44
36	2.10	0.89	-0.19
42	2.15	0.95	-0.15
48	2.16	0.94	-0.42
54	2.24	1.10	-0.32
60	2.20	0.98	-0.31
66	2.39	1.22	-0.05
72	2.23	1.11	-0.60

It can be concluded that recursive strategy is suitable for tasks where the forecasting horizon is small, while for larger forecasting horizons the MIMO strategy is more appropriate.

VI. CONCLUSION

This study presents two different strategies (recursive and MIMO) for forecasting the power generated by a PV power plant using the LSTM neural network. Analyzing and comparing the two strategies, the following results were obtained.

The dataset used in the prediction process consists of 5-years in-filed production data measurements collected from the CETATEA photovoltaic power plant, a research site facility for renewable energies located in Cluj-Napoca, Romania.

The evaluation on the testing dataset of the two strategies considered 3 metrics: RMSE, MAE and MBE. Although the values obtained for RMSE on the testing dataset are higher than those obtained on the validation dataset, the differences are not significant. Furthermore, the MAE indicates that the average distance between the actual and predicted value does not exceed 1.91 kW for the recursive strategy and 1.22 kW for MIMO one, proving their performance on future data.

On the other hand, MBE evaluates the model from another perspective, its negative values indicating the tendency of both strategies to underestimate the results.

The recursive strategy has better performance for small forecasting horizons, while MIMO is suitable for bigger forecasting horizons. The MIMO strategy is more stable with the increase of the forecasting horizon, the accumulation of errors being avoided by having a sequence of real values to predict the next sequence.

In the case of the recursive strategy, the accuracy of the model was improved when it was trained using a bigger dataset, meaning that in time, after collecting more data, the model performance will be improved. On the other hand, in the case of MIMO strategy the best results were obtained using only one year of data for training.

The regression using time steps and the regression using window technique were analyzed for one-step ahead forecasting model and it was proved that regression using time steps provides better result than the other architecture.

Furthermore, the models presented here not just that satisfy the needs of the market, but based on the results obtained, problems such as the energy crisis can be avoided, providing better management of energy and monitoring the lifetime of photovoltaic panels.

Finally, the models analyzed in this study are univariate models. Future research will include multi-variate models which takes into consideration not only the PV power generated in the past, but also other factors which influence the production of PV energy such as temperature, solar irradiance, and cloud cover.

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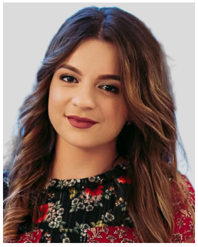

RALUCA NELEGA was born in Deva, Hunedoara, Romania, in May 2000. She is currently pursuing the bachelor's degree in telecommunications technologies and systems with the Faculty of Electronics, Telecommunications and Information Technologies, Technical University of Cluj-Napoca, Romania.

She is also a Research Assistant with the National Institute for Research and Development of Isotopic and Molecular Technologies. Her main research interests include machine learning techniques in spectrum sensing and energy prediction.

DAN IOAN GREU was born in Ludus, Târgu Mures, Romania, in 2000. He is currently pursuing the bachelor's degree in electronics, telecommunications and information technology with the Technical University of Cluj-Napoca.

His research interests include study of machine learning algorithms and their role in predicting the performance of power plants and future power losses caused by unknown reasons.

EUSEBIU JECAN received the bachelor's degree in electronics, telecommunications and information technologies from the Technical University of Cluj-Napoca (TUC-N), Romania, in 2015, and the Master of Science degree in electronics, telecommunications and information technologies from TUC-N, where he is currently pursuing the Ph.D. degree with the Communications Department.

He has been an Assistant Professor with the Communications Department, TUC-N, since 2017. As an Assistant Professor, he teaches software engineering classes, specifically C/C++, Java, MySQL, and JavaScript. He has published three papers, indexed in the Web of Science (one ISI journal article and two ISI proceeding papers) and one indexed in BDI. He contributed as a researcher to two international and one national research project. His research interests include the Industrial IoT networks, software engineering, and AI.

VASILE REDNIC received the Ph.D. degree in physics from Osnabrück University, Germany, and Babes-Bolyai University, Cluj-Napoca, Romania, in 2010.

Since 2008, he has been a Scientific Researcher and then a Technology Development Engineer with the National Institute for Research and Development of Isotopic and Molecular Technologies. Since 2020, he has been holding a position of the Deputy Director of the Center for Advanced Research and Technologies for Alternative Energy (CETATEA). He was a coordinator of two research projects and a member of ten national and international projects. He has published 28 papers, indexed in web of science, one patent granted, and two other patent requests.

CIPRIAN ZAMFIRESCU received the B.Sc. and M.Sc. degrees in electronics and telecommunications from the University Politehnica of Bucharest, in 2013 and 2016, respectively, where he is currently pursuing the Ph.D. degree in 5G, connected drones and IoT technologies and their impact on everyday life and global industry. He successfully prepared and presented a bachelor's thesis based on Spatial Multiplexing MIMO system with a real-life test-bed implementation and a master's thesis focused on Carrier Aggregation Technology in LTE-Advanced.

He was involved in many telecom industry projects as 4G/5G network deployment for mobile network operators. He is also a part-time researcher and a subject-matter expert in different projects in the university environment. He built the one of the first end-to-end instant mobile coverage solution from a drone using AI to serve remote areas search and rescue missions. His main research interests include 5G, the IoT, digital transformation, industry 4.0, AI, machine learning, automation, big data, SDR, SDN, virtualization, networks, sensors, programming languages, blockchain, quantum communications, hardware test-beds implementations, and physical experiments.

EMANUEL PUSCHITA (Member, IEEE) received the Ph.D. and Habilitation degrees in electronics, telecommunications and information technologies from the Technical University of Cluj-Napoca (TUC-N), Romania, in 2009 and 2017, respectively.

He has been with the Communications Department, TUC-N, since 2002, where he is currently a Full Professor. He is also a Course Coordinator of cellular radio communications, communication systems, and radio network planning. He has published over 70 ISI-WOS journal articles and ISI-WOS proceedings papers and three patent requests. He was also a coordinator of four national projects, a member of seven international research projects, and a member of 14 national competition projects.

Prof. Puschita is a member of IEEE Aerospace and Electronic Systems Society and IEEE Antennas and Propagation Society. He is currently holding a position of the Chapter Vice-Chair of the IEEE Romania Section–Antennas and Propagation Society/Council of RFID Joint Chapter.

ROMULUS VALERIU FLAVIU TURCU received the B.Eng. and Doctoral degrees in physics from Babes-Bolyai University, Cluj-Napoca, Romania, in 2001 and 2007, respectively.

From 2010 to 2012, he was a Scientist with the Pacific Northwest National Laboratory (PNNL), a U.S. Department of Energy Laboratory. Since 2017, he has been an Associate Professor with the Physics Department, Babes-Bolyai University. He was the co-founder and the managing director of two startup companies. Since October 2019, he has been the President and the CEO of the National Institute for Research and Development of Isotopic and Molecular Technologies. He has published over 65 articles, 43 being indexed in the Web of Science/ISI journals and holds two U.S. Patents.