BİTLİS EREN ÜNİVERSİTESİ
FEN BİLİMLERİ DERGİSİ

ISSN: 2147-3129 / e-ISSN: 2147-3188

Article Type	: Research Article	**Year**	: 2025
Received	: November 8, 2024	**Volume**	: 14
Revised	: June 10, 2025	**Issue**	: 2
Accepted	: June 10, 2025	**Pages**	: 677-696
DOI	: [10.17798/bitlisfen.1581731](https://doi.org/10.17798/bitlisfen.1581731)		

VERY SHORT-TERM SOLAR POWER FORECASTING USING HYBRID LSTM-SVM

Tuba TANYILDIZI AĞIR [1*]

[1] *Batman University, Department of Electronics and Automation, Batman, Türkiye,*
tuba.tanyildiziagir@batman.edu.tr

ABSTRACT

Solar energy is one of the most preferred energy sources among renewable energy sources. Very short-term power forecasting has an important role in the voltage and frequency control of solar energy. However, it provides stability to energy by correcting energy fluctuations in the energy market. In this study, long short term memory (LSTM), support vector machines (SVM) and hybrid LSTM-SVM model were used to estimate PV power in the very short term. The inputs of the models were 60-minute pressure, humidity, temperature, cloudiness and wind speed of Şanlıurfa province in 2022.At the output of the models, the 60-minute power value of the PV panel was obtained. The performances of hybrid LSTM-SVM, LSTM and SVM were compared using mean square error (MSE), root mean square error (RMSE), normalized root mean square error (NRMSE), mean absolute error (MAE) and correlation coefficient (R). In the very short term, PV panel power Hybrid LSTM-SVM, SVM, and LSTM predicted 0.9649, 0.8836 and 0.7255, respectively. The proposed hybrid LSTM-SVM model outperformed the classical LSTM and SVM. The performance metrics of the hybrid LSTM-SVM model, MSE, RMSE, NRMSE, MAE and R, were 9.0098e-04, 0.0300, 0.0318, 0.011 and 0.9823, respectively. The hybrid LSTM-SVM model had high stability and accuracy in very short-term solar power forecasting. Hybrid LSTM-SVM can be used as an alternative method for very short-term solar power forecasting.

Keywords: Photovoltaic panel, Very-short-term power forecast, LSTM, SVM, Hybrid LSTM-SVM.

1 INTRODUCTION

The demand in renewable energy resources has increased due to reasons such as the decrease in traditional energy resources, air pollution, the development of technology, the increase in world population and industrialization. Among renewable energy resources, solar energy is the most preferred type of energy [1]. Solar energy is the largest renewable energy resource and the source of energy for many other energy types. Solar energy is a clean energy as it does not emit pollutant emissions [2]. The energy generated by PV panels depends on meteorological conditions such as rainfall, snow, wind, cloudiness, humidity, and solar radiation [3]. Since the energy produced by PV panels depends on weather conditions, it is difficult to estimate PV power. If PV is predicted correctly, it balances supply and demand, facilitates the management of energy, minimizes operating costs, and ensures the safe operation of the network [4]. Solar energy forecasts are categorized as very- short-term forecasts, short-term forecasts, medium-term forecasts, and long-term forecasts. While long-term solar energy forecasts are used in the management of energy, medium-term solar energy forecasts are used in business decisions such as energy agreements and day-ahead scheduling. While short-term solar energy forecasts are used to overcome uncertainties in renewable energy, very-short-term solar energy forecasts, on the other hand, are used in voltage and frequency control applications [5]. Besides, very-short-term energy forecasting is extremely important for energy marketers and retailers in business transactions of companies [6].

Limouni et al. proposed a hybrid model consisting of an LSTM-temporal convolutional neural network (TCN) to forecast very-short-term PV power. The LSTM-TCN hybrid method was compared with LSTM, TCN. The performance of the Hybrid LSTM-TCN model was better than the LSTM and TCN model. The error metrics of the proposed hybrid model, MAE, RMSE, and mean bias error (MBE) were 0.428, 1.122, and -0.0141 respectively [7].Rana et al. used a univariate model and a multivariate model in order to forecast the solar power at 5 minutes and 60 minutes ahead. The univariate model and the multivariate model performed similarly and the average relative error was 4.15-9.34% [3]. Rafati et al. proposed a method based on univariate data for the forecast of very-short-term solar energy. The proposed method was compared with neural network (NN), support vector regression, and random forest. The prediction accuracy of the proposed model was better than the compared models. The minimum and maximum errors of the proposed method, MAE, RMSE, and mean relative error were 2.6-4.99, 6.93-21.97, and 0.11-0.29, respectively [6]. Kushwaha and Pindoriya proposed a hybrid method consisting of seasonal autoregressive integrated moving average (SARIMA)-random vector functional link (RVFL) neural network supported by maximum overlap discrete wavelet transformation for the forecasting of very-short-term PV energy. The hybrid method was compared with SARIMA, W-SARIMA, RVFL, W-RVFL, and SVR. The hybrid SARIMA-RVFL model predicted solar panel better than the compared models. MAPE, RMSE, mean absolute scaled error and coefficient of determination (R^2) of hybrid SARIMA-RVFL were 23.846, 1.054, 0.711 and 0.899, respectively [8]. Dokur proposed a hybrid method using swarm decomposition and feed forward neural network (SWD-FFNN) to forecast PV energy at 15-minute intervals. The hybrid SWD-FNN method, RMSE MSE were 0.0362 ,0.0013 respectively [9]. Yildiz and Acikgoz proposed a kernel extreme learning machine (KELM) for the forecasting of very-short-term energy. KELM compared with levenberg marquardt and extreme learning machine (ELM). The error metrics R, RMSE and MAE of the KELM model were 0.851, 12.51 and 7.5, respectively. The KELM algorithm showed a more reliable prediction performance than other compared methods [1]. Chen et al. proposed radiation classification coordinate (RCC) - LSTM for very-short-term power forecasting. The performance of the hybrid RCC-LSTM model was compared with RCC-BPNN, RCC-Elman, RCC-RBFNN and LSTM. The MAE percentage of the RCC-LSTM hybrid model was between 2.74% and 7.25%. It had a higher accuracy compared to other models [10].

Monfared et al. added a traditional fuzzy-based method to the Wang model algorithm for 15-minute PV power forecasting. The proposed method was compared with the fuzzy method and ANN. The hybrid method outperformed the compared models with an NRMSE of 3.6% [11]. Kothona et al. developed a hybrid ensemble long short-term memory (ELSTM)-FFNN model for forecasting solar energy at 15-minute and 60-minute intervals. Hybrid ELSTM-FNN increased the prediction accuracy of the model between 3-11.9% and 0.2-17.8% [12]. Kim et al. used a LSTM-recurrent neural network (RNN) to forecast PV energy in the very-short-term. The proposed model showed good performance and the RMSE value was 13.478. Experimental results showed that the hybrid LSTM-RNN method could be used for forecasting [13].Golestaneh et al. used the ELM method to forecast PV energy at 10-minute and 60-minute intervals. The RMSE and MAE values of ELM were 7.67% and 4.16%, respectively. This method obtained reliable prediction results [14]. Jaidee and Pora used deep neural network(DNN), gated recurrent unit (GRU) and CuDNNGRU to forecast PV energy in the very-short-term. When compared to other models, the GRU model achieved the lowest RMSE of 7.83% [15].

Table 1 is showed the models that predict the power of the solar panel in the short term. The RMSE of the Hybrid SWD-FNN model was 0.0362 while the RMSE of the Hybrid LSTM-SVM model was 0.0300. The prediction performance of the current study and Dokur’s [9] study were very close to each other. However, the current study performed better than many models in the literature.

Table 1. Comparison of literature.

Reference	Model	R^2	RMSE	MAE	NRMSE
Limouni et al.[7]	Hybrid LSTM-TCN	-	1.122	0.428	-
Kushwaha and Pindoriya[8]	Hybrid SARIMA-RVFL	0.899	1.054	-	-
Dokur[9]	Hybrid SWD-FNN	-	0.0362	-	-
Yildiz and Acikgoz[1]	KELM	-	12.51	7.53	-
Chen et al.[10]	Hybrid RCC-LSTM	-	-	2.74-7.25	-
Monfared et al.[11]	Fuzzy	-	-	-	3.6
Kothona et al.[12]	Hybrid ELSTM-FNN	-	1.060-1.552	0.433-0.659	-
Kim et al.[13]	Hybrid LSTM-RNN	-	13.478	-	-
Golestaneh et al.[14]	ELM	-	7.67	4.16	-
Jaidee and Pora[15]	GRU	-	7.83	-	-
Current study	**Hybrit LSTM-SVM**	**0.9649**	**0.0300**	**0.011**	**0.0318**

The main contributions of this study are as follows:

- A hybrid LSTM-SVM model consisting of LSTM and SVM models was developed.
- In the literature, many models have been used to estimate PV panel power in the very short term. However, in the literature, the Hybrid LSTM-SVM model has not been used to estimate PV panel power in the very short term. The developed hybrid LSTM-SVM model was more successful than many models used in the literature.
- The performance of the hybrid LSTM-SVM model was compared with the traditional LSTM and SVM algorithm. The performance of the hybrid LSTM-SVM model outperformed the LSTM and SVM model.
- MSE, RMSE, NRMSE, and MAE were used to classification the performance of the hybrid algorithm and single algorithms.
- Regression analysis was performed to compare the accuracies of hybrid LSTM-SVM, LSTM and SVM.

2 MATERIAL AND METHOD

In Section 2.1, Data was described. In Section 2.2, LSTM was presented. In Section 2.3, SVM was explained. In Section 2.4, Hybrid LSTM-SVM model was described.

2.1 Data

The data used in this study was obtained from a PV power generating 1.175MW of power and connected to the network in Şanlıurfa, Türkiye. Figure 1 was shown an image of the PV power. The data were recorded at 60-minute intervals from January 1, 2022, to March 30, 2022. From this data, we filtered the data between 07:00 in the morning and 18:00 in the evening. Data was recorded during 11 hours of the day. This data set was recorded at 60-minute intervals over a 3-month time period and a total of 947 data were collected. In Figure 2 was showed the time-power graph of the PV panel. As seen in the figure, the power produced by the PV panel was not stable and varied over time. Technical details of the facility were presented in Table 2. The rated power, total string capacity, daily energy, lifetime energy and specific energy of these panels were 1020kW, 1.175MWp, 6.152MWh, 8.895GWh and 5.24 kWh/kWp, respectively. On the day that solar energy is produced, 8,868 kt of carbon dioxide gas in the atmosphere decreases. However, the exact location and name of the power plant were restricted by the authorities. For this reason, only some technical details and images were presented. In this study, weather variables such as pressure, humidity, temperature, cloudiness and wind speed were monitored at 60-minute intervals. Meteorological data were obtained from the General Directorate of the Ministry of Environment, Urbanization and Climate Change of the Republic of Turkey. Data from January 1, 2022, to March 30, 2022 were used. However, in Table 3, 3-day data set was given.The lower and upper limits of the input values are given below.

$$936.5 \leq \text{Pressure} \leq 959.4$$

$$21 \leq \text{Moisture} \leq 99$$

$$3 \leq \text{Heat} \leq 22.3$$

$$0 \leq \text{Cloudiness} \leq 8$$

$$0.1 \leq \text{Wind} \leq 5.3$$

Figure 1. Images of the PV power plant.

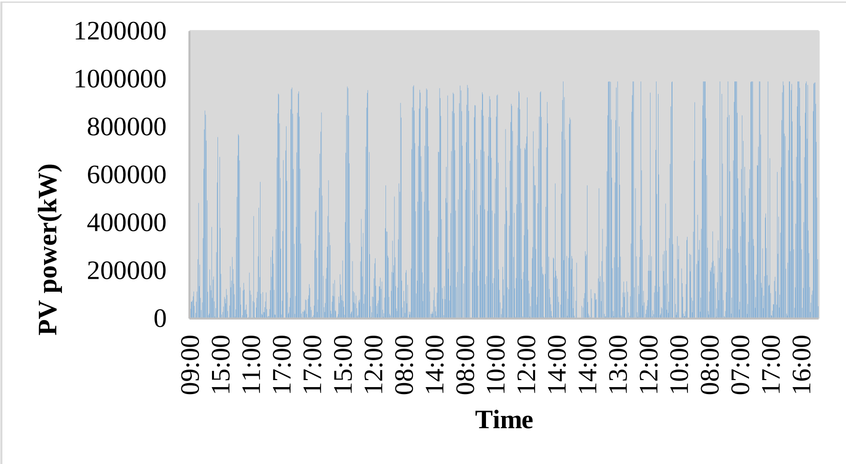

Figure 2. PV power-time.

Table 2. Technical details of the PV panel.

Technical Details	Value
Country	Türkiye
City	Şanlıurfa
Rated Power	1020 kW
Total String Capacity	1.175 MWp
Daily Energy	6.152 MWh
Lifetime Energy	8.895 GWh
Specific Energy	5.24 kWh/kWp
CO_2 Reduction	8.868 kt

Table 3. Meteorological data.

Pressure	Moisture	Heat	Cloudiness	Wind Speed	PV power
956.2	78.0	5.8	5	1.7	28387
955.5	83.0	6.1	5	1.2	40300
954.8	79.0	6.1	7	0.6	70467
954.6	80.0	7.2	7	0.8	69729
954.7	72.0	7.3	5	0.7	74938
954.8	73.0	6.9	5	0.8	92108
954.8	76.0	6.8	5	0.4	113417
954.9	78.0	6.6	5	0.1	53079
955.0	77.0	5.9	5	0.4	5218
951.7	64.0	8.3	5	0.7	23806
950.7	59.0	8.9	5	0.5	69651
950.1	58.0	9.8	4	0.5	112335
949.5	54.0	11.0	2	0.8	247661
949.5	55.0	9.6	4	1.2	482709
949.8	76.0	7.3	7	1.6	135980
949.7	82.0	7.1	7	1.3	224778
949.7	83.0	7.3	7	1.4	85830
949.6	81.0	7.5	7	1.2	34728
949.6	79.0	7.5	7	1.2	4053
952.0	37.0	8.0	0	1.2	67704
951.6	34.0	8.3	0	1.9	335805
951.4	31.0	10.7	0	1.8	625625
951.3	26.0	10.8	0	2.8	789893
951.3	30.0	11.7	0	2.3	867925
951.6	28.0	10.8	0	1.9	850787
951.9	25.0	9.5	3	1.7	742493
952.5	31.0	8.4	3	0.9	493183
953.1	37.0	7.3	0	0.7	111541
953.6	39.0	6.7	0	1.2	13829

2.2 Long Short Term Memory

The LSTM network is an advanced form of RNN. The RNN looks just like a tree and is used to place consecutive data. RNN improves its learning ability by preserving the data collected in the previous step. However, in the long run, its performance is not very good during back-propagation computation. The LSTM network is proposed to improve the RNN [16]. In Figure 3, LSTM and RNN networks were shown. The LSTM network consists of four gates: input gate, output gate, forget gate and update gate. The Forget gate decides what to forget; the input gate decides what to add to the neuron; the update gate updates according to new information; and, the output gate functions to generate long-term memory. At a given time, the long and short-term memory accepts a sequence of inputs. It generates the sequence of outputs according to the new long-term memory and the new short-term memory [17].

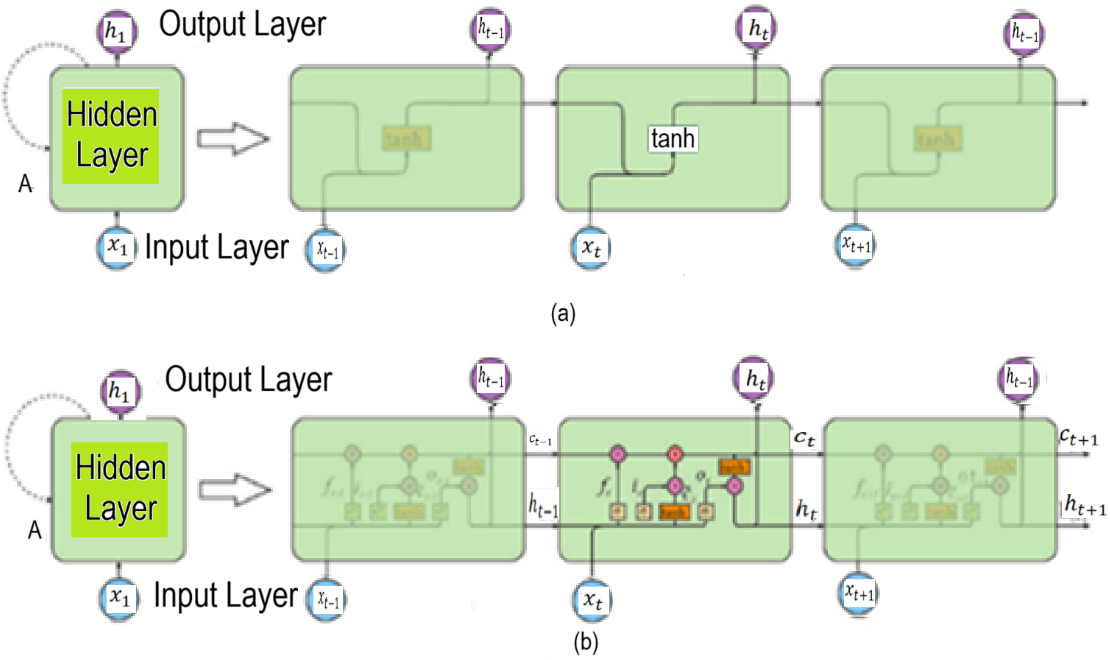

Figure 3. (a) RNN network; (b) LSTM network [18].

In Equation 1, the weight matrix and the bias matrix were shown.

$$W = \begin{bmatrix} W_f \\ W_i \\ W_o \end{bmatrix}, b = \begin{bmatrix} b_f \\ b_i \\ b_o \end{bmatrix} \tag{1}$$

W and b represent the weight and bias matrices respectively. The sub-indices, i and f, refer to the output gate, the input gate and the forget gate respectively. In Equation 2, the forget gate was shown. The first layer of the LSTM was the forget gate; it forgets unnecessary information and remembers necessary information.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{2}$$

f_t refers to the forget gate, on the other hand, σ refers to a sigmoid activation function ranging between 0 and 1. In the forget gate, 1 means to save everything while 0 means to forget everything.x_t refers to the time period t of the input. h_{t-1} represents the t-1 step of the output. W_f and b_f refer to the bias matrix and the weight matrix, respectively. The input layer decides which of the new information should be stored. The input layer was given in Equation 3.

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

i_t is the input layer. While W_i is the weight vector of the input layer, b_i is the bias value of the input layer. The new candidate vector was presented in Equation 4.

$$\widetilde{C_t} = \tanh\left(W_c.\left[h_{t-1}, x_t\right] + b_c\right) \tag{4}$$

$\widetilde{C_t}$ represents the new candidate values. While W_c is the weight of the candidate vector, b_c is the bias value of the candidate vector. Equation 5 was referring to the activation function.

$$tanhx = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{5}$$

tanh is refers to the hyperbolic tangent activation function between -1 and 1. The new candidate vector was presented in Equation 6.

$$C_t = f_t.C_{t-1} + i_t.\widetilde{C_t} \tag{6}$$

C_t is the current cell while C_{t-1} represents the previous cell state. In Equation 7, the last layer, the output layer, was shown. The output layer was presented in Equation 8.

$$o_t = \sigma\left(W_0\left[h_{t-1}, x_t\right] + b_o\right) \tag{7}$$

$$h_t = o_t.\tanh\left(C_t\right) \tag{8}$$

This layer is a filtered version of the current cell state. In the LSTM network, the decision layer, sigmoid, is run first to decide which part of the cell to output. We put tanh in the cell and multiply it by the output of the sigmoid.o_t , W_o, and b_o represent the output gate, weight matrix and bias matrix respectively. h_t represents the input of the next state [18].

The most suitable parameters for training the LSTM model were obtained as a result of hyperparameter adjustment. The hyperparameters of the LSTM model are hidden layer, activation function, learning rate, speed, number of epochs, batch size, etc. The random search method was used to obtain the hyperparameters of the LSTM model. Many experiments were conducted to obtain the best training options. Table 4 was presented the training parameters of the LSTM model. As seen in the table, the learning rate, max epoch, mini batch size, iteration and training elapsed time of the LSTM model were 0.1, 400, 60, 5600 and 1min 40 sec, respectively.The training time of the LSTM model was very short.

Table 4. Training Options of the LSTM model.

Training Options	Adam
Max Epochs	400
Mini Batch Size	60
Initial Learn Rate	0.1
Learn Rate Schedule	Piecewise
Learn Rate Drop Period	1000
Learn Rate Drop Factor	0.000001
Training elapsed time	1 min 40 sec
Epoch	400
Iteration	5600
Iterations per epoch	14
Frequency	50 iterations
Hardware resource	Single GPU
Learning rate schedule	Piecewise

2.3 Support Vector Machines

SVM is a binary classifier that makes forecasts by converting the input data into a high-dimensional database. For each classification, a non-marginal hyperplane is created and two possible output classes are obtained. The working principle of SVM is that it takes small-sized input data and creates a high-dimensional feature space with a nonlinear matching function. The newly formed dataset is reorganized as a linear problem and then a linear classification is performed. The most crucial step in SVM classification is to select the appropriate kernel for the problem. Because each kernel generates SVM with different properties. Since each SVM consists of different kernels, its performance also differs. There are three types of kernels in SVM: radial basis function, linear kernel and polynomial kernel [19]. SVM performs a good generalization, minimizes possible errors, and minimizes the over adaptation problem. It also combines learning with optimization in order to minimize structural errors [20]. The regression function of the SVM model was given in equation 9.

$$f(x) = \omega\varphi(x) + b \tag{9}$$

f(x) is the regression function. *X* represents the input vector, *φ(x)* is the high-dimensional feature space transformed from the input vector, *ω* is the weight vector, and *b* shows the deviation amount.The regularized risk function was given in Equation 10. The tube size of SVM was given in equation 11.

$$R(C) = C\frac{1}{n}\sum_{i=1}^{n} L(d_i, y_i) + \frac{1}{2}\|\omega\|^2 \tag{10}$$

$$L_\varepsilon(d, y) = \begin{Bmatrix} |d - y| - \varepsilon |d - y| \geq \varepsilon \\ 0 \quad otherwise \end{Bmatrix} \tag{11}$$

C refers to the penalty parameter, $\frac{1}{2}\|\omega\|^2$ refers to the adjustment term, d_i shows to the number of observations of the desired term, $C\frac{1}{n}\sum_{i=1}^{n} L(d_i, y_i)$ refers to the error term, and ε shows to the tube size expressed in L_ε. Equation 12 was defined lagrange multipliers.

$$f(x, \alpha_i, \alpha_i^*) = \sum_{i=1}^{n} (\alpha_i, \alpha_i^*)\, K(x, x_i) + b \tag{12}$$

The kernel function was given in Equation 13.

$$K_{rbf}(x, x_i) = \exp\left[\frac{-(x - x_i)^2}{2\sigma^2}\right] \tag{13}$$

$K\ (x,\ x_i)$ shows to the kernel function. σ refers to the standard deviation of the data [21].

Table 5. SVM model parameters.

Max objective evaluations	**30**
Total function evaluations	30
Total elapsed time	133.1168 seconds
Total objective function evaluation time	125.6116
Observed objective function value	0.00481
Estimated objective function value	0.0047906
Function evaluation time	0.06582
Estimated function evaluation time	0.063183
Epsilon	0.024076
Box Constraint	0.20116
Kernel Scale	2.5485

Table 5 was showed the parameters of the SVM model. According to the SVM model, the best estimated feasible points were epsilon, box constraint and kernel scale, respectively 0.024076, 0.20116 and 2.5485. In order to obtain the parameters of the model, the hyperparameters must be adjusted. The hyperparameters of the SVM model are the regularization parameter (C) and Gamma (γ). C is the penalty parameter of the error term. γ is the inverse of the effective radius of the support vectors. If C and γ are selected large, it causes overfitting, while if C and γ are selected small, it causes misclassification. In this study, the random search method was used to adjust the hyperparameters of the SVM model. In the random search, the best hyperparameters are searched randomly to obtain them. In this study, C_{min}, C_{max}, γ_{min} ve γ_{max} hyperparameters were obtained as follows as a result of the random search.

$$C_{min} = 0.01, C_{max} = 10$$

$$\gamma_{min} = 0.001, \gamma_{max} = 0.1$$

2.4 Hybrid LSTM-SVM

In this study, a hybrid LSTM-SVM algorithm was developed for very short-term solar energy forecasting. LSTM and SVM models were used to estimate solar energy. However, LSTM and SVM model solar energy estimates were 0.7255 and 0.8836 respectively. These estimates were not very satisfactory. Therefore, when the prediction performance was evaluated by combining both models, it was observed that the prediction performance of the hybrid model was good.

The inputs of the algorithm were pressure, humidity, temperature, cloudiness and wind speed, sampled at 60-minute intervals, while the outputs of the algorithms were PV panel power. In Figure 4, the flow diagram of the hybrid LSTM-SVM showed. Data set consisting of meteorological data was presented as input data to the hybrid algorithm. Initially, the normalization process started for the data set. SVM optimized the dataset and started the pre-processing process. Preprocessing is the process of cleaning the data. SVM model created a framework for outlier data. In this study, the quartile range (IQR) method was used for preprocessing. Outliers need to be removed before training the model. Outliers can be sampling errors, experimental errors, data entry errors, natural outlier errors and measurement errors. 1st Quartile was defined as Q_1 (25% quartile), 3rd Quartile was defined as Q_3(75% quartile). The lower limit in the data set was defined as $Q_1 - 1.5IQR$ ve üst sınır ise and the upper limit was defined as $Q_3 - 1.5IQR$. As a result of this process, 47 outliers were eliminated. After the iteration process was completed, the newly created data set was presented to the input of the LSTM algorithm. The LSTM algorithm divided the data set into two parts, 90% as the training data and 10% as the testing data. Testing and training continued until the iteration was completed. After completion of the iteration, MSE, RMSE, NRMSE, MAE and R error metrics were obtained. The hybrid LSTM-SVM algorithm estimated PV panel power at 60-minute intervals. When the hybrid learning model algorithm was finished, the SVM and LSTM algorithms were run with the same data set. SVM and LSTM algorithms estimated PV panel power at 60-minute intervals.

Table 6. Training parameters of the hybrid LSTM-SVM model.

Training Options	Adam
Max Epochs	2000
Mini Batch Size	150
Initial Learn Rate	0.002
Learn Rate Schedule	Piecewise
Learn Rate Drop Period	100
Learn Rate Drop Factor	0.001
Gradient Threshold	1
Hardware Resource	Single GPU
Learning Rate	0.1
Epoch	2000
Maximum Iteration	10000

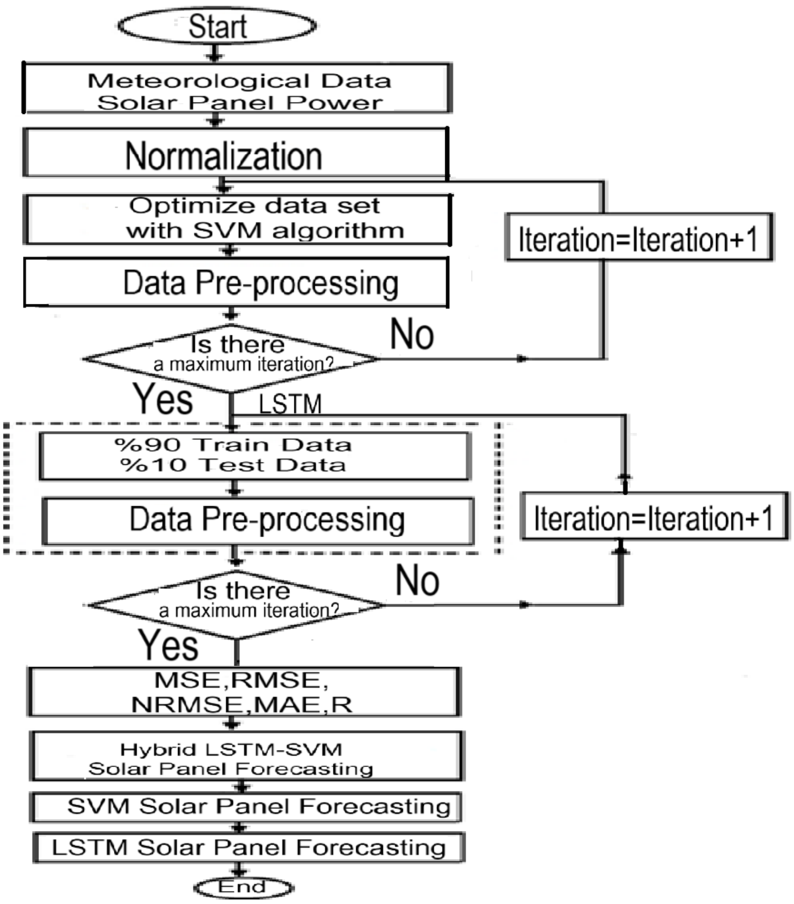

Figure 4. Flow diagram of the Hybrid LSTM-SVM algorithm.

Table 6 was shown the parameters of the hybrid LSTM-SVM, LSTM, SVM model. The maximum epochs, mini batch size, initial learn rate, learning rate and maximum iteration of the hybrid LSTM-SVM model were 2000, 150, 0.002, 0.1 and 10000, respectively. Since the number of iterations of the hybrid LSTM-SVM model was high, the training time was also long.

3 RESULTS AND DISCUSSION

Section 3.1 performance metrics was described. Section 3.2 Simulation results was explained.

3.1 Performance Metrics

MAE, MSE, RMSE and NRMSE, R were used to determine the performance of this study. F_i is the observed value. O_{bi} is the estimated value.

- MAE: It is a metric used to assess the performance of renewable energy. It is the absolute value of the difference between the actual value and the forecasted value. The equation of MAE was given in Equation 14.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|F_i - O_{bi}| \tag{14}$$

- MSE: It shows the mean square of the difference between the actual value and the forecasted value. The equation of MSE was given in Equation 15.

$$MSE = \left(\frac{1}{n}\sum_{i=1}^{n}(F_i - O_{bi})^2\right) \tag{15}$$

- RMSE: It is the root mean square root of the squared difference between the actual value and the forecasted value. In this metric, errors are squared before being averaged. Therefore, more emphasis is placed on large errors in this metric. RMSE is used when significant errors are unwelcome. The equation of RMSE was given in Equation 16.

$$RMSE = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(F_i - O_{bi})^2\right)} \tag{16}$$

- NRMSE: It is the normalized form of RMSE. In Equation 17, NRMSE was presented [22].

$$NRMSE = \frac{RMSE}{mean} = \sqrt{\sum_{i=1}^{n} \frac{(F_i - O_{bi})^2}{O_{bi}}} \tag{17}$$

- Correlation coefficient was given in Equation 18.

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}(F_i - O_{bi})^2}{\sum_{i=1}^{N}(F_i)^2}} \tag{18}$$

3.2 Simulation Results

In this study, LSTM, SVM and hybrid LSTM-SVM algorithms were used to forecast the energy generated by the PV panels at 60-minute intervals. The performance metrics of these algorithms were MSE, RMSE, NRMSE, MAE and R. The data were divided into two categories: training data and testing data. Table 7 was presented the error metrics and regression results for the training data of Hybrid LSTM-SVM, LSTM and SVM. The very short-term PV power predictions of LSTM, SVM and hybrid LSTM-SVM models for training were 0.5489, 0.8669 and 0.9739. The hybrid LSTM-SVM model for training showed better prediction performance than LSTM and SVM. The SVM algorithm also had better prediction accuracy than LSTM. The error metrics MSE, RMSE, NRMSE, MAE and R for the training data of the hybrid LSTM-SVM algorithm were 9.0267e-04, 0.0300, 0.0329, 0.0122 and 0.9869, respectively. The hybrid LSTM-SVM model was successful in predicting PV power at 60-minute intervals for the training data. In Table 8, error metrics for the testing data of Hybrid LSTM-SVM, LSTM and SVM were shown. The very short-term PV power estimates for the test data of LSTM, SVM, and hybrid LSTM-SVM models were 0.7255, 0.8836, and 0.9649, respectively. The hybrid LSTM-SVM model performed better than the models compared for the test data. The error metrics of MSE, RMSE, NRMSE, MAE and R for the test data of the hybrid LSTM-SVM algorithm were found to be 9.0098e-04, 0.0300, 0.0318, 0.011 and 0.9823, respectively. The hybrid LSTM-SVM model achieved the best prediction value with minimum error compared to other models for both test and training data.

Table 7. Performance metrics for the training data of Hybrid LSTM-SVM, LSTM and SVM.

Training	MSE	RMSE	NRMSE	MAE	R	R^2
LSTM	0.0273	0.1651	0.1811	0.0764	0.7648	0.5489
SVM	0.0048	0.0693	0.075	0.0397	0.9311	0.8669
Hybrid LSTM-SVM	**9.02e-04**	**0.030**	**0.0329**	**0.0122**	**0.9869**	**0.9739**

Table 8. Performance metrics for the testing data of Hybrid LSTM-SVM, LSTM and SVM.

Training	MSE	RMSE	NRMSE	MAE	R	R^2
LSTM	0.0120	0.1095	0.1160	0.049	0.8518	0.7255
SVM	0.0030	0.0545	0.0577	0.0335	0.9400	0.8836
Hybrid LSTM-SVM	**9.009e-04**	**0.0300**	**0.0318**	**0.011**	**0.9823**	**0.9649**

In Figure 5, error metrics for the training data of the LSTM, SVM and hybrid LSTM-SVM model were presented. LSTM model obtained larger MSE, RMSE, NRMSE and MAE values for training data than other models. The LSTM model was poorer than other models in predicting PV power in the very short term for the training data. The hybrid LSTM-SVM model achieved minimum MSE, RMSE, NRMSE and MAE for the training data. It shows that the hybrid LSTM model has good accuracy in predicting PV power in the very short term. Figure 6 was shown the MSE, RMSE, NRMSE and MAE for the test data of LSTM, SVM hybrid LSTM-SVM models. The error metrics for the LSTM model test data were large. The error metrics for the SVM model test data were smaller than LSTM. The error metrics for the hybrid LSTM-SVM model test data were smaller than the compared models. The hybrid LSTM-SVM model achieved minimum error metrics for both training and testing data. Figure 7 was showed the regression values of LSTM, SVM and hybrid LSTM-SVM algorithm. The regression values of LSTM, SVM, and hybrid LSTM-SVM algorithm were 0.7648, 0.9311, and 0.9869, respectively. The predicted values of the LSTM algorithm were quite far from the regression line. It showed that this algorithm has poor very short-term prediction accuracy of the PV panel. The predicted values of the SVM algorithm were not very close to the regression curve. The dependent variable of the hybrid LSTM-SVM model was close to the dependent variable. It showed that the prediction accuracy of the hybrid LSTM-SVM model was good. The hybrid LSTM-SVM model was successful in predicting PV panel power in the very short term.

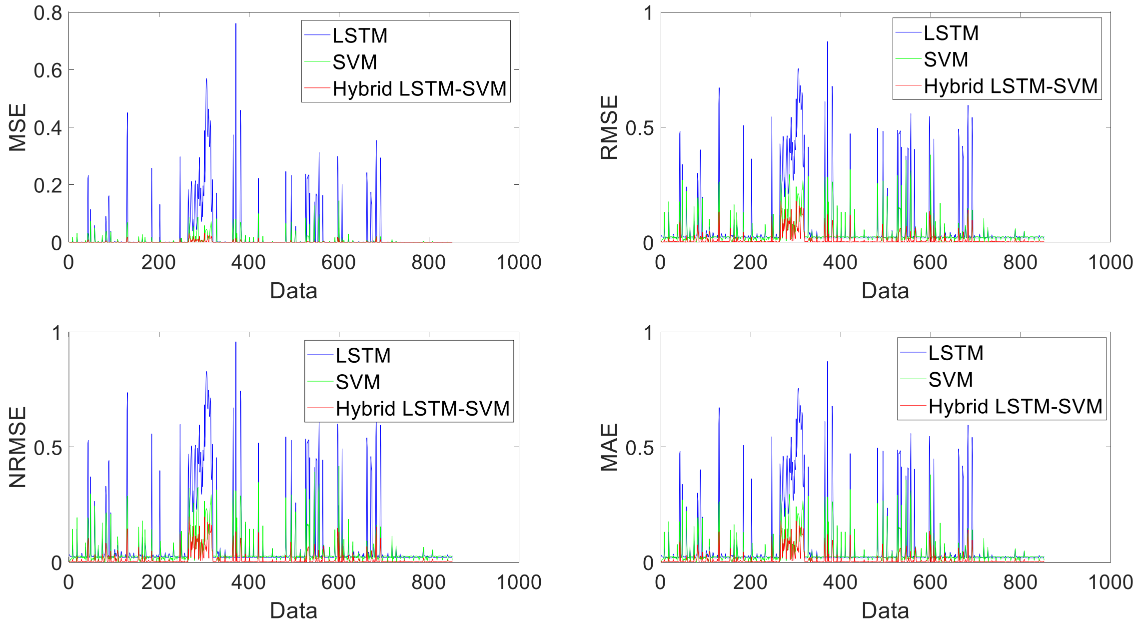

Figure 5. Error metrics of LSTM, SVM and Hybrid LSTM-SVM algorithm for the training data.

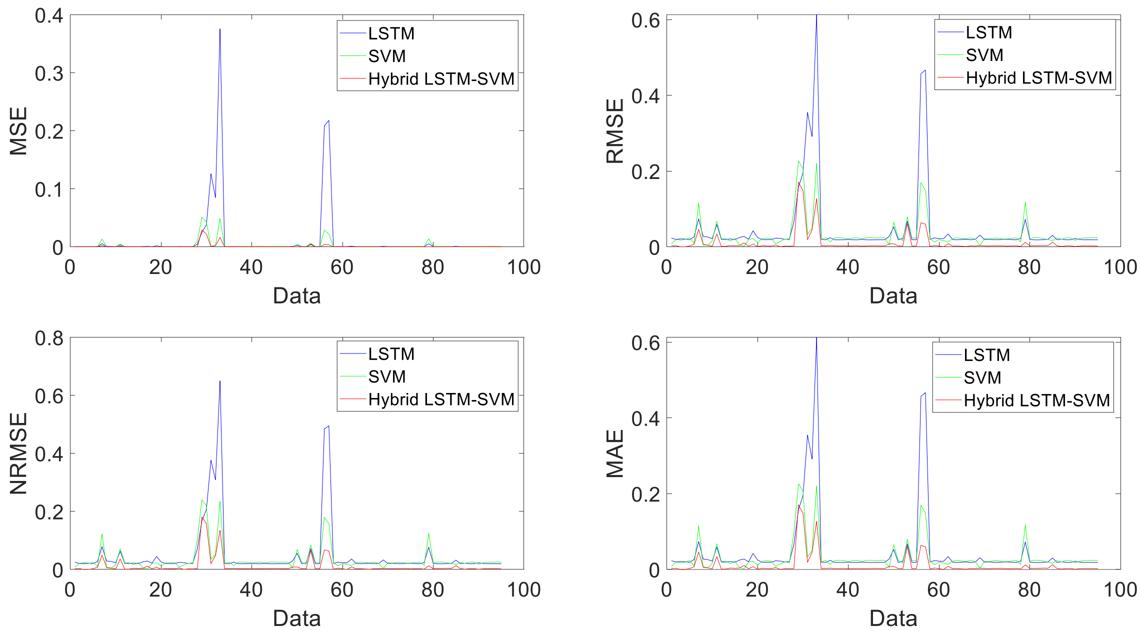

Figure 6. Error metrics of LSTM, SVM and Hybrid LSTM-SVM algorithm for the testing data.

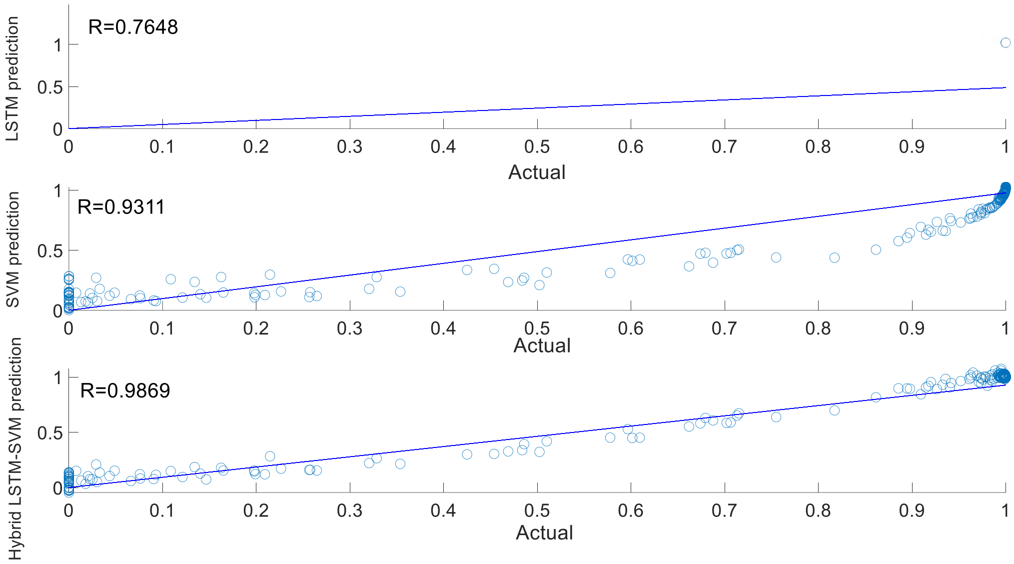

Figure 7. Regression curves of LSTM, SVM, Hybrid LSTM-SVM

4 CONCLUSION AND SUGGESTIONS

In this study, hybrid LSTM-SVM model was developed to predict PV power in the very short term. To compare the performance of the hybrid model, LSTM and SVM models were used. The prediction accuracies of the models for both test and training data were evaluated with MSE, RMSE, NRMSE, MAE and R. The very short term PV power forecasts of LSTM, SVM and hybrid LSTM-SVM models were compared with the help of regression curves. The prediction accuracies of LSTM, SVM and hybrid LSTM SVM models were 0.7255, 0.8836 and 0.9649, respectively. The hybrid LSTM-SVM model was better than the LSTM and SVM models in predicting PV power in the very short term. The MSE, RMSE, NRMSE and MAE values of the hybrid LSTM-SVM model were 9.009e-04, 0.0300, 0.0318 and 0.011, respectively. Regression analysis showed that the hybrid LSTM-SVM model had better prediction accuracy than other models. The results showed that when LSTM, SVM models were combined, the performance of the hybrid model was better than the single models. However, the computational time of Hybrid LSTM-SVM model was longer than LSTM and SVM. The SVM model was more successful than the LSTM model in predicting PV power in the very short term. Parameter tuning can be done to improve the performance of the LSTM model. Hybrid LSTM-SVM model can be a different option for PV power in the very short term. The constraints of this study were: 60-minute data of Şanlıurfa province for the year 2022.The constraints are important in terms of the model's running time, performance and generalizability. When the constraint is selected large, it causes processing complexity, while when it is selected small, the model's performance decreases. In the future study, the Hybrid LSTM-SVM model will be used to estimate PV power in the short term in multiple regions. Thus, the generalizability of the Hybrid LSTM-SVM model will be clarified. Hybrid LSTM-SVM model can be used in frequency and voltage control with very short-term energy forecasting. In future studies, very short-term performance will be evaluated by combining different models with LSTM.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

REFERENCES

[1] C. Yildiz & H. Acikgoz H., "A kernel extreme learning machine-based neural network to forecast very short-term power output of an on-grid photovoltaic power plant, energy sources", *Part A: Recovery, Utilization, and Environmental Effects*, vol.43, no.4, pp.395-412, 2021.

[2] F. Barbieri, S. Rajakaruna &A. Ghosh A., "Very short-term photovoltaic power forecasting with cloud modelling: A review", *Renewable and Sustainable Energy Reviews*, vol.75, pp.242-263, 2017.

[3] M. Rana, I. Koprinska & V. G. Agelidis, "Univariate and multivariate methods for very short-term solar photovoltaic power forecasting", *Energy Conversion and Management*, vol.121, pp.380-390, 2016.

[4] A. Mellit, A. M. Pavan & V. Lughi V., "Deep learning neural networks for short-term photovoltaic power forecasting", *Renewable Energy*, vol.172, pp.276-288, 2021.

[5] H. Panamtash, S. Mahdavi, Q.Z. Sun, G.J. Qi, H. Liu & A. Dimitrovski, "Very short-term solar power forecasting using a frequency incorporated deep learning model", *IEEE Open Access Journal of Power and Energy,* vol.10, pp.517-527, 2023.

[6] A. Rafati, M. Jordanian, E. Mashhour & H.R. Shaker, "High dimensional very short-term solar power forecasting based on a data-driven heuristic method", *Energy,* vol.219, pp.119647, 2021.

[7] T. Limouni, R. Yaagoubi, K. Bouziane, K. Guissi & E.H. Baali, "Accurate one step and multistep forecasting of very short-term PV power using LSTM-TCN model", *Renewable Energy*, vol.205, pp.1010-1024, 2023.

[8] V. Kushwaha & N.M. Pindoriya, "A SARIMA-RVFL hybrid model assisted by wavelet decomposition for very short-term solar PV power generation forecast", *Renewable Energy*, vol.140, pp.124-139, 2019.

[9] E. Dokur, "Swarm decomposition technique based hybrid model for very short-term solar PV power generation forecast", *Elektronika ir Elektrotechnika*, vol.26, no.3, pp.79-83, 2020.

[10] B. Chen, P. Lin, Y. Lai, S. Cheng, Z. Chen & L. Wu, "Very-short-term power prediction for PV power plants using a simple and effective RCC-LSTM model based on short term multivariate historical datasets", Electronics, vol.9, no.2, pp.289, 2020.

[11] M. Monfared, M. Fazel, R. Lewis & J. Searle, "Fuzzy predictor with additive learning for very short-term PV power generation", *IEEE Access*, vol.7, pp.91183-91192, 2019.

[12] D. Kothona, I.P. Panapakidis & G.C. Christoforidis, "A novel hybrid ensemble LSTM-FFNN forecasting model for very short-term and short-term PV generation forecasting", *IET Renewable Power Generation*, vol.16, no.1, pp.3-18, 2022.

[13] D. Kim, D. Kwon, L. Park, J. Kim & S. Cho, "Multiscale LSTM-based deep learning for very-short-term photovoltaic power generation forecasting in smart city energy management", *IEEE Systems Journal*, vol.15, no.1, pp.346-354, 2020.

[14] F. Golestaneh, P. Pinson H.B. & Gooi H.B., "Very short-term nonparametric probabilistic forecasting of renewable energy generation—With application to solar energy", *IEEE Transactions On Power Systems,* vol.31, no.5, pp.3850-3863, 2016.

[15] S. Jaidee &W. Pora W, "Very short-term solar power forecasting using genetic algorithm based deep neural network", *In 2019 4th International Conference on Information Technology 2019*.

[16] X. Song, Y. Liu, L. Xue, L. J. Wang, J. Zhang, J. Wang, ... & Z. Cheng, "Time-series well performance prediction based on Long Short-Term Memory (LSTM) neural network model", *Journal of Petroleum Science and Engineering*, vol.186, pp.106682, 2020.

[17] K.E. Arun Kumar, D.V. Kalaga, C.M.S. Kumar, M. Kawaji & T.M. Brenza, "Forecasting of COVID-19 using deep layer recurrent neural networks (RNNs) with gated recurrent units (GRUs) and long short-term memory (LSTM) cells", *Chaos, Solitons & Fractals*, vol.146, pp.110861, 2021.

[18] R. Huang, C. Wei, B. Wang, J. Yang, X. Xu, S. Wu& S. Huang, "Well performance prediction based on Long Short-Term Memory (LSTM) neural network", *Journal of Petroleum Science and Engineering*, vol.208, pp.109686, 2022.

[19] Y. Xu, B. Klein, G. Li & B. Gopaluni, "Evaluation of logistic regression and support vector machine approaches for XRF based particle sorting for a copper ore", *Minerals Engineering*, vol.192, pp.108003, 2023.

[20] R. Dehghani, H. Torabi Poudeh, H. Younesi & B. Shahinejad, "Daily streamflow prediction using support vector machine-artificial flora (SVM-AF) hybrid model", *Acta Geophysica*, vol.68, pp.1763-1778, 2020.

[21] J.Fan, J. Zheng, L. Wu & F.Zhang, "Estimation of daily maize transpiration using support vector machines, extreme gradient boosting, artificial and deep neural networks models", *Agricultural Water Management*, vol. 245, pp.106547, 2021.

[22] N. Elizabeth Michael, M. Mishra, S. Hasan & A. Al-Durra, "Short-term solar power predicting model based on multi-step CNN stacked LSTM technique", *Energies*, vol.15, no.6, pp.2150, 2022

[23] A.B. Çolak, Ö. Açıkgöz, H. Mercan, A.S.Dalkılıç & S. Wongwises, "Prediction of heat transfer coefficient, pressure drop, and overall cost of double-pipe heat exchangers using the artificial neural network", *Case Studies in Thermal Engineering*, vol.39, pp.102391, 2022.