Derin Öğrenme Tabanlı Sıcaklık ve Nem Tahmini

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Makale Bilgileri	ÖZ
	Havanın sıcaklık ve nem parametreleri canlı yaşamı başta olmak üzere tarım, ulaşım gibi birçok alanı etkilemektedir. Bu sebepten dolayı bu parametrelerin gelecekteki değerlerini doğru tahmin etmek önemlidir. Bu çalışmada, Tekirdağ ili Süleymanpaşa ilçesi için oluşturulan model sistem üzerinden ve Meteoroloji İl Müdürlüğünden alınan sıcaklık ve nem veri setleri kullanılarak, derin öğrenme tekniklerinden LSTM algoritmaları ile sıcaklık ve nem tahmini yapılmıştır. Tek sensör üzerinden alınan verilerde gürültü kaynaklı hatalardan dolayı çoklu sensörlerden gelen veriler birleştirilerek veri seti oluşturulmuştur. 2015-2021 yılları arasındaki Tekirdağ Meteoroloji İl Müdürlüğünden alınmış sıcaklık ve nem verileri, oluşturulan model sistem üzerinden alınan 2020 yılına ait sıcaklık ve nem verileri ile sensör füzyonu uygulanarak veri seti elde edilmiştir. Bu veri seti ile 2022 yılına ait sıcaklık ve nem verileri derin öğrenme algoritmaları ile tahmin edilmiştir. Zamana göre sıralı olarak gelen veriler için derin öğrenme algoritmalarından Long Short Term Memories (LSTM) kullanılmıştır. Tahmin edilen veriler yine Tekirdağ Meteoroloji İl Müdürlüğünden alınan 2022 yılına ait gerçek veriler ile karşılaştırılmıştır. Bu tahminde başarı ölçütleri olarak RMSE 1.895, MSE 3.547, R-kare skoru değerinin 0.952 ve MAE 1,614 olarak hesaplanmıştır. Zamana göreli sıralı biçimde gelen verilerde bu algoritmanın kullanılabileceği görülmüştür. Oluşturulan model sistem PLC ve SCADA tabanlıdır.

Deep Learning Based Temperature and Humidity Prediction

Article Info	ABSTRACT
	The temperature and humidity parameters of the weather influence various fields, including living conditions, agriculture, and transportation. Hence, accurately predicting the future values of these parameters is important. In this study, temperature and humidity forecasts were made using deep learning techniques, specifically LSTM algorithms, through a model system created for the Süleymanpaşa district of Tekirdağ province. Temperature and humidity datasets were obtained from the Meteorology Provincial Directorate and integrated with data from multiple sensors to mitigate errors caused by noise in single-sensor data. Temperature and humidity data from the Tekirdağ Meteorology Provincial Directorate between 2015 and 2021 were merged with the 2020 temperature and humidity data obtained from the model system to create a fused dataset. Using this dataset, temperature and humidity data for the year 2022 were predicted using deep learning algorithms. Long Short-Term Memory (LSTM) algorithms were utilized for sequentially ordered data over time. The predicted data were then compared with actual data from the Tekirdağ Meteorology Provincial Directorate for the year 2022. The success metrics for these predictions were calculated as RMSE of 1.895, MSE of 3.547, an R-squared score of 0.952, and an MAE of 1.614. The results suggest that this algorithm can be employed for sequentially ordered data over time. The model system developed is based on PLC and SCADA technology.

INTRODUCTION

Weather parameters, particularly temperature and humidity, play a crucial role in various domains, including life, agriculture, transportation, and more. The global issues of climate change and global warming are impacting many areas of our world. Therefore, it is highly important to accurately predict the future values of temperature and humidity [1].

There are numerous applications developed today that rely on a single type of sensor. However, using a single type of sensor has significant disadvantages. It often leads to partial information about the operating environment, continuous errors due to noise in measurements, and the potential for errors to impact the entire system[2]. Instead of relying on data from a single source, combining and synthesizing data from different sources eliminates these limitations. Overcoming the constraints of data from individual sensors is possible by integrating data from multiple sensors [3]. Sensor fusion operations are complex. Taking the average of data from different sources is referred to as data fusion, which involves combining data from different sources.

The word "fusion" refers to the concepts of merging, merging, sensor coordination, and control [4]. Multiple sensor fusion consists of data fusion, sensor planning, and system architecture. In the upper layer, sensor inputs are accompanied by four auxiliary processes: human-computer interaction, database management, resource pre-processing [5].

Deep learning, also known as deep neural networks, is a machine learning technique that exhibits characteristics similar to the human brain, such as observation, analysis, learning, and decision-making[6]. It can perform tasks like data classification, transformation, and feature identification. Deep learning techniques have found applications in various fields, particularly in computer science. With advancements in computer architecture, algorithm-driven deep learning techniques have reached impressive levels of performance. Unlike classical methods, which often require mathematical expressions, deep learning techniques offer more accurate results and predictions [7].

Deep learning architectures vary depending on the dimension, type, and structure of the input data[8]. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Restricted Boltzmann Machines (RBM), and Deep Belief Networks (DBN) are among the most commonly used architectures[9].

In the literature, according to the study by Wenshu Zha et al., LSTM algorithms were employed to predict monthly gas production from a gas field, and they determined the success rate [10]. In the work of Jingwei Hou et al., they used a dataset created from 60,133 hours of meteorological data (including temperature, dew point, air pressure, wind direction, wind speed, and cloud amount) obtained from the Yinchuan weather station in China from January 2000 to October 2020. They utilized the LSTM algorithm to make hourly predictions and calculated the success rate [11]. In the study by Karabulut et al., they used meteorological data from the province of Kars between 2010 and 2021 with the LSTM algorithm to make monthly and daily predictions [12].

In this study, temperature and humidity data for the Süleymanpaşa district of Tekirdağ province in Turkey were first obtained from the Tekirdağ Meteorology Provincial Directorate for the years 2015-2021. Temperature and humidity data for the year 2020 were obtained from the created model system. Due to errors in the data from a single sensor, sensor fusion was applied to obtain a dataset. After normalizing the collected data, temperature and humidity predictions for the year 2022 were made using an LSTM algorithm trained on the model. The accuracy of the results was compared with the data obtained from the Tekirdağ Meteorology Provincial Directorate for the year 2022, and a success value was obtained.

MATERIALS AND METHODS

Hardware Infrastructure

In the model system, two PT 100 RTD (Resistance Temperature Detector) sensors and one Dwyer temperature sensor with a 0-10 Volt output were used to measure temperature. PT 100 temperature sensors are preferred in sensitive applications due to their high accuracy and stable outputs. The resistance value

of PT 100 sensors changes by 0.39 Ω for every 1˚C increase or decrease, starting from a resistance value of 100 Ω at 0˚C. The measurement temperature range is from -40°C to +60°C [13]. A Dwyer brand humidity sensor with a 0-10 Volt output was used to measure ambient humidity. The humidity sensor is known for its stable output, sensitivity, and the ability to provide both current and voltage outputs using the built-in DIP switch. These are the key features of the humidity sensor.

The sensors used in this study were connected to the Wago 750-852 model PLC. The Wago 750-852 PLC, designed for Ethernet/IP and Modbus communication, supports all PLC programming languages according to the IEC 61131-3 standard. The Wago PLC and its modules used in the study are shown in Table 1, and the PLC SCADA interface is illustrated in Figure 1.

Table 1. *PLC and modules*

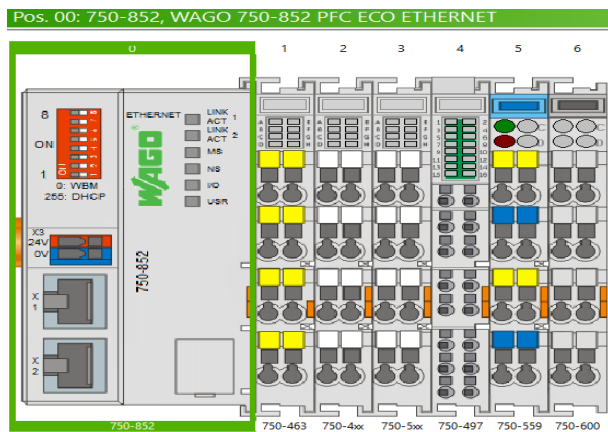| Number	Modul Names	Modul Properties
0	750-852	CPU
1	750-463	4 AI RTD
2	750-430	8 DI 24V DC
3	750-530	8 DO 24V DC
4	750-497	8 AI 0-10 V
5	750-559	4 AO 0-10 V DC
6	750-600	End Module

Figure 1. *Wago 750-852 PLC*

The PT100 temperature sensor of the RTD module is connected to the first two inputs of the module, while the other temperature sensor is connected to the first input of the AI module. The humidity sensor used in the model system is connected to the second channel of the 750-497 AI module.

LSTM (Long Short Term Memory)

The Long Short-Term Memory (LSTM) algorithm is a recurrent neural network (RNN)-based deep learning method that was initially introduced by Hochreiter and Schmidhuber [14]. LSTM overcomes the difficulties encountered in training deep learning models. Its key advantage in sequential or time series problems is its ability to learn long-term dependencies and handle memory through its specialized gating mechanism [15].

In the block diagram of the LSTM cell shown in Figure 2, X represents the current inputs, H represents the previous hidden state, and C represents the previous memory state. In the outputs from the LSTM cell, H represents the current hidden state, and C represents the current memory state [16].

In the LSTM architecture, the input gates, denoted as I, are represented by Equation 1, the forget gates, denoted as f, are represented by Equation 2, the memory cells, denoted as Ct, are represented by Equation 3, and the output gates, denoted as Ot, are represented by Equation 4. The LSTM algorithm has been highly successful in time series prediction and classification applications [17].
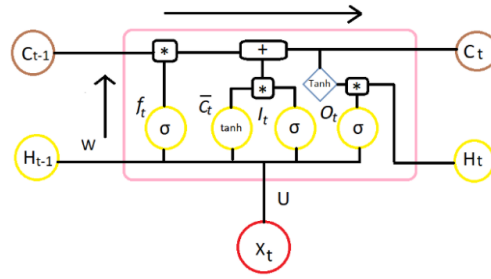
Figure 2. *Block diagram of an LSTM cell at time.*

$$I_t = \sigma(W_{xi}X_t + W_{hi}H_{t-1} + W_{ci}C_{t-1} + b_i) \tag{1}$$

$$ft = \sigma(W_{xf}X_t + W_{hf}H_{t-1} + W_{cf}C_{t-1} + b_f) \tag{2}$$

$$Ct = f_t \odot C_{t-1} + I_t \odot \tan H(W_{xc}X_t + W_{hc}H_{t-1} + b_c) \tag{3}$$

$$Ot = \sigma(W_{xo}X_t + W_{ho}H_{t-1} + W_{co}C_t + b_o) \tag{4}$$

Preparation of Data

Normalization is the process of making the output data more efficient. The goal at this stage is to ensure the creation of the necessary datasets. In the normalization process, techniques such as Median, Sigmoid, Z-Score, and Min-Max are used[18].

$$z = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{5}$$

In this study, the Min-Max normalization technique was used. The temperature and humidity data from the Meteorology Tekirdağ Provincial Directorate, covering the years 2015-2021, were obtained along with the data from the model system for the year 2020. To utilize these data for deep learning, the necessary scaling was performed using the min-max formula given in Equation 5, ensuring that the values were scaled between 0 and 1.

Table 2 provides temperature and humidity data for the year 2020. The values in the first and second columns are obtained from Tekirdağ Meteorology Provincial Directorate. The temperature and humidity values in the third and fourth columns are obtained from the PLC and SCADA-based model system that has been developed.

AUTOMATION MODEL

PLCs (Programmable Logic Controllers), which are microprocessor-based devices that perform traditional control functions, are indispensable in industrial systems. Real-time monitoring of processes and storage of data from field equipment are important tasks of SCADA (Supervisory Control and Data Acquisition) systems [19].

The open source editor Codesys, developed by 3SMART, was used to program the PLC used in the model system. Codesys is the common software development editor of several PLC manufacturing companies[20]. The CFC (Continius Function Chart) programming language was used in the temperature and humidity sensor interfaces created for this study.

In the Codesys software interface shown in Figure 3, the average of the values from two PT 100 temperature sensors and one temperature sensor with a 0-10V output is calculated. The first sensor, named Temperature_Sensor1, is connected to the first channel of the RTD module, while Temperature_Sensor2 is connected to the second channel of the same RTD module. The sensor named Temperature_Sensor3 is connected to the first channel of the 750-497 8AI module. To minimize errors caused by noise in data from a single sensor, the average of the values from the three sensors is taken.

Table 1. *Example of the raw data used in the learning model for the year 2020*

No	Date	Temperature (°C)	Humidity (%Rh)	Temperature (°C) Wago	Humidity (% Rh) Wago
1	1.01.2020	4.9	67.2	4.6	67.6
2	2.01.2020	3.9	67.3	4	67.5
3	3.01.2020	4.2	66	4.6	65.6
4	4.01.2020	6.7	60.9	7.1	61.2
5	5.01.2020	5.8	72.6	5.9	72.8
6	6.01.2020	4.9	72.4	4.9	72.1
7	7.01.2020	2.2	76.6	2.1	76.9
8	8.01.2020	1.4	67.8	1.6	67.6
9	9.01.2020	3.3	63.2	3.6	63
10	10.01.2020	4.8	67.8	4.6	68.1
11	11.01.2020	5.8	76.9	6	77
12	12.01.2020	8.3	74	8.6	73.8
13	13.01.2020	5.8	74.2	6	74.6
14	14.01.2020	5	74.3	5.3	74.5
15	15.01.2020	5.8	74.9	5.6	74.5
16	16.01.2020	8.1	70.9	7.8	70.9
17	17.01.2020	7.3	71.8	7.6	72.2
18	18.01.2020	5.9	75.9	5.8	75.9
19	19.01.2020	6.4	71.1	6.3	71
20	20.01.2020	4.5	68.8	4.2	68.4
21	21.01.2020	2.8	67.5	3.1	67.5
22	22.01.2020	2.8	72.9	2.5	72.8
23	23.01.2020	6.2	64.2	6.2	64.5
24	24.01.2020	3.8	63.5	3.6	63.3
25	25.01.2020	5.5	71.3	5.7	71.3
26	26.01.2020	8.8	77	8.9	76.9
27	27.01.2020	9.3	83.8	9.2	84.1
28	28.01.2020	9.9	82.8	10.3	83
29	29.01.2020	9.5	79.4	9.5	79.4
30	30.01.2020	8.6	73.3	8.4	73.1
31	31.01.2020	6.8	67.7	7	67.3
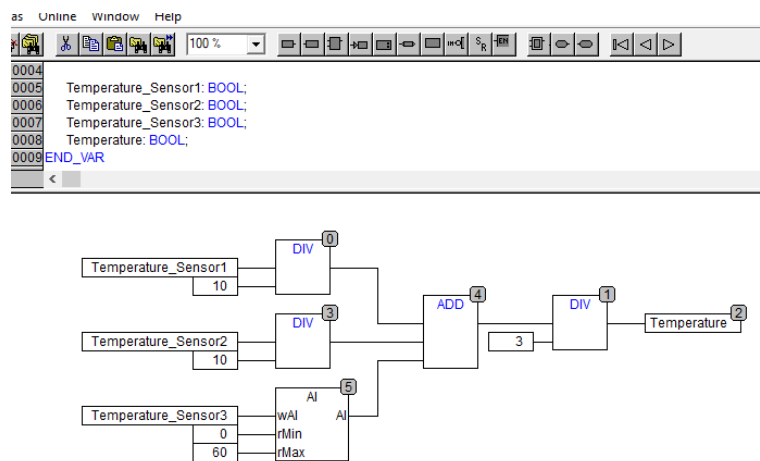
Figure 3. *Codesys temperature measurement interface software*

For reading data from the Dwyer brand 0-10V humidity sensor used in the model system, the interface software created in Codesys is shown in Figure 4. An AI function block is used to convert the sensor's output value to a humidity range of 0 to 100 percent. This block multiplies the incoming value by 100 and divides it by the digital maximum value of 32.768 to calculate the ambient humidity value.
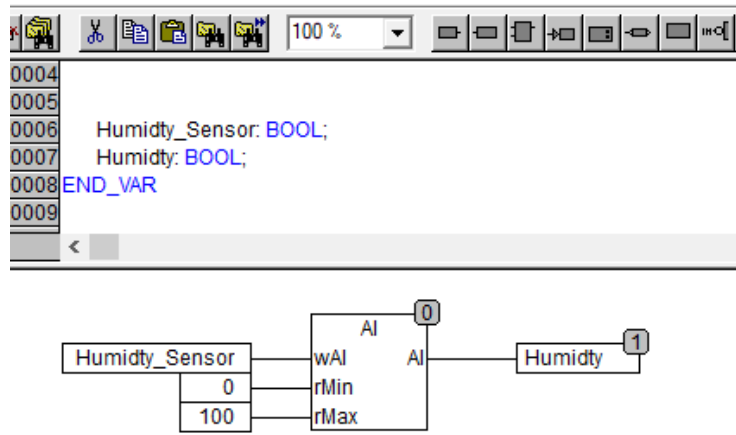
Figure 4. *Codesys humidity measurement interface*

The ambient temperature and humidity data obtained from the Codesys interface were recorded in the database of the Visu SCADA software using the Modbus TCP/IP protocol at ten-minute intervals. The resulting data has been saved in Excel format. The labels created using Visu SCADA are shown in Figure 5. When creating the tags, temperature sensors and humidity sensor are selected as Word data type. According to the Modbus address structure, analog addresses start with zero.

Figure 5. *Visu Scada modbus TCP/IP tags*

The SCADA screen interface created in the Visu-SCADA software, along with these variables, is shown in Figure 6.
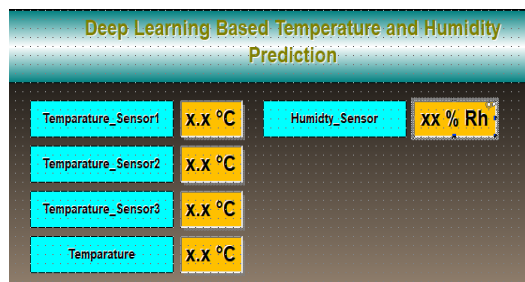

Figure 6. *Visu Scada interface screen*

The development, testing, and prediction processes of the model were carried out using the Tensorflow library in the Python language. Tensorflow is a Python-based library commonly used for machine learning and deep learning models, providing various functionalities [21]. For these processes, the Spyder interface within the Anaconda platform was used.

In the created model system, data for the year 2020 was obtained. The data from 2015 to 2021 was obtained from the Tekirdağ Meteorology Provincial Directorate. These two datasets were combined using sensor fusion. The obtained dataset was imported into a DataFrame using the read_csv function from a CSV file. Real-time graphs can be plotted for the acquired data, and the graphs for the predictions can also be generated. The predictions can be saved in Excel format. To prepare the data and create the desired

prediction graphs, the code block provided in Figure 7 was used.

```
    df = pd.read_csv('tekirdag.csv')
    df.head()
    df['Date'] = pd.to_datetime(df.Date,format='%Y-%m-%d')
    df.index = df['Date']
    plt1.figure(figsize=(16,8))
    plt1.plot(df['Temperatures'], label=Temperatures L)
    plt1.ylabel('Data')
    plt1.xlabel('Date(01.01.2022- 31.12.2022)')
    plt1.title("Temperatures ", y=1.0, loc='left')
```

Figure 7. *Code example*

TRAINING THE MODEL AND FORECASTING

After completing the training, evaluation, and testing processes of the obtained dataset consisting of 2558 rows and 4 columns, the prediction process for the year 2022 was conducted. The prediction included temperature and humidity values for 2022. The graphical representation of the daily average temperature values obtained from the prediction is shown in Figure 8, and the predicted humidity values for the year 2022 are presented in Figure 9.

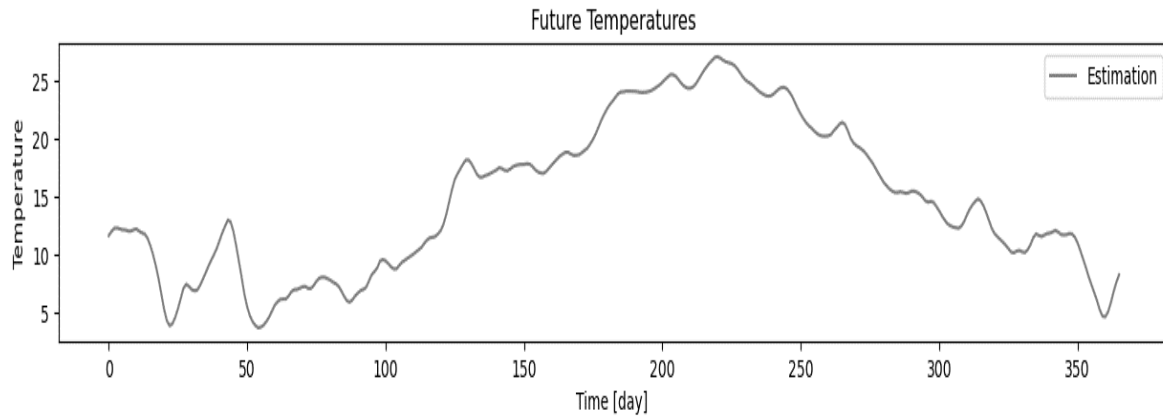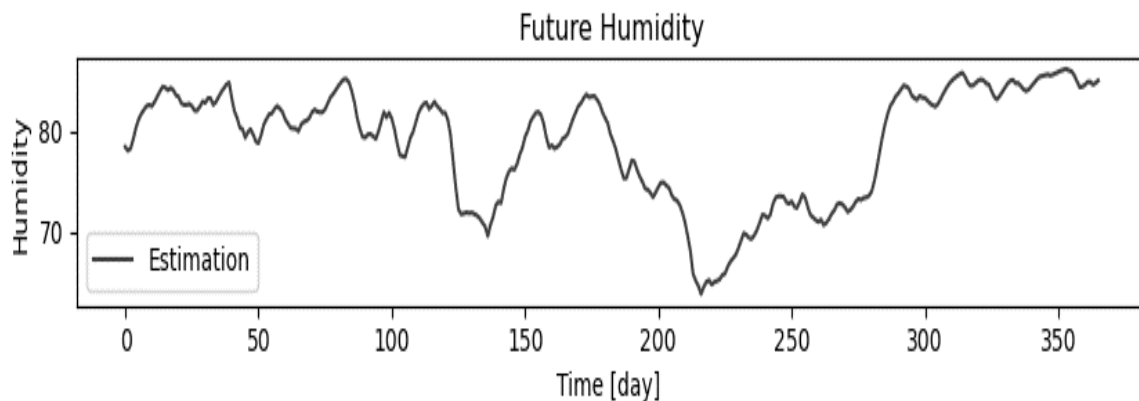**Figure 8.** *Graphical display of predicted temperature data for 2022*

Figure 9. *Graphical display of predicted humidity data for 2022*

The numerical values of the temperature and humidity predictions, along with the corresponding actual values obtained from the Tekirdağ Meteorology Provincial Directorate, for the first three days of each month in 2022 are given in Table 3.

Table 3. *Some predicted values for temperature and humidity for 2022 and real values*

Date	Humidity (Predicted) (%)	Temperature (Predicted) (°C)	Humidity (Real) (%)	Temperature (Real) (°C)
1.01.2022	83.3964	8.6950	84.8	7.3
2.01.2022	80.045	11.058	82.5	10.3
3.01.2022	84.245	10.326	83.5	9.5
…				
1.02.2022	73.181	5.935	75.0	5.9
2.02.2022	85.306	6.008	87.2	5.8
3.02.2022	82.562	4.406	82.9	3.7
…				
1.03.2022	75.840	5.201	76.4	6.3
2.03.2022	72.131	3.699	74.8	2.6
3.03.2022	70.717	5.993	70.3	5.1
…				
1.04.2022	79.322	6.734	55.6	16.7
2.04.2022	79.636	6.955	55.5	18.1
3.04.2022	62.673	13.053	61.7	14.9
…				
1.05.2022	75.775	13.159	74.3	14.6
2.05.2022	75.083	13.733	74.6	14.0
3.05.2022	80.627	13.583	82.0	12.4
…				
1.06.2022	76.987	22.895	76.0	22.0
2.06.2022	70.902	22.853	71.9	23.0
3.06.2022	66.357	22.687	65.2	23.6
…				
1.07.2022	70.750	23.996	69.3	24.4
2.07.2022	72.656	24.290	71.0	25.1
3.07.2022	68.987	24.623	66.8	24.7
…				
1.08.2022	68.140	24.750	68.2	26.0
2.08.2022	70.919	25.141	71.8	25.1
3.08.2022	66.225	25.549	67.8	25.6
…				
1.09.2022	76.806	24.964	77.5	25.4
2.09.2022	82.416	24.498	81.2	25.8
3.09.2022	75.552	24.359	77.5	24.4
…				
1.10.2022	76.523	21.927	77.5	21.5
2.10.2022	62.994	22.618	62.8	23.0
3.10.2022	52.284	18.278	55.9	18.8
…				
1.11.2022	81.393	14.553	80.5	14.8
2.11.2022	84.695	14.433	85.2	14.0
3.11.2022	83.223	15.380	82.6	15.0
…				
1.12.2022	87.681	13.522	88.5	12.8
2.12.2022	90.689	11.841	90.4	10.0
3.12.2022	87.400	10.707	88.1	9.2

PERFORMANCE METRICS

In the conducted study, performance metrics such as RMSE (Root Mean Square Error), MSE (Mean Squared Error), R2 (R-squared score), and MAE (Mean Absolute Error) values have been calculated. Where (y)ˆpredicted value of y, y‾mean value of y.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2} \tag{6}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2 \tag{7}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \tag{8}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}| \tag{9}$$

RMSE, expressed by Equation 6, is the square root of the average of squared errors for the predicted values. RMSE, which is a crucial performance criterion, can vary between zero and infinity [22]. The Mean Squared Error (MSE), indicated by Equation 7, is one of the measurement criteria, and its value approaching zero signifies better prediction accuracy [23]. The R-squared score, represented by Equation 8, demonstrates the equality between actual and predicted values and ranges between 0 and 1. The closer this value is to 1, the more successful the prediction [24]. MAE, denoted by Equation 9, quantifies the difference between actual and predicted values. Here, t represents the expected value, and a represents the actual value [25].

In this study, the RMSE value is calculated as 1.895, the MSE value is 3.547, the R-squared value is 0.952, and the MAE value is calculated as 1.614.

CONCLUSIONS

Deep learning has brought significant advancements in solving artificial intelligence problems in recent times. One of the most important reasons for this is the need for large amounts of computation. The contribution of hardware architectures has also led to this development. With advancing technology, sensors can generate and store a vast amount of data. The accuracy of the data obtained through sensor fusion has further improved. A model system based on PLC and SCADA has been established to evaluate the data from sensors. In this model system, temperature and humidity data from the year 2020 have been collected. PLC and SCADA-based systems are indispensable in modern automation systems. Having abundant data is a desirable condition for the accuracy of predictions made using deep neural networks.

In this study, average temperature and humidity data for 2558 days between January 1, 2015, and December 31, 2021, were used. The obtained data was scaled to the range of 0-1 and subjected to min-max normalization. The training, testing, and prediction processes of the deep learning model were carried out using the Spyder interface in the Anaconda platform. In the LSTM model, various techniques were tried by altering the number of neurons and layers, and finally, in the experiment with 4 input dimensions, the best result was achieved with 10 neurons and 2 layers. By training the LSTM neural network that combines data from two different sources, temperature and humidity predictions for 365 days in the year 2022 were made. These predictions were compared with the data obtained from the Tekirdağ Meteorology Provincial Directorate for the year 2022. In this study, the RMSE value is calculated as 1.895, the MSE value is 3.547, the R-squared value is 0.952, and the MAE value is calculated as 1.614. It was observed that successful predictions were obtained as a result. This method can be applied to data obtained over time.

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