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Effect of environmental factors on Solar-panel Power Loss and Photovoltaic Performance

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ABSTRACT

Solar energy as the most important source of renewable energy is an important alternative to fossil and non-renewable energies which is highly related to the environmental changes. The power output delivered from a photovoltaic module depends on the amount of irradiance which reaches the solar cells. Many factors determine the ideal output or optimum yield in a photovoltaic module which can be classified to climatological, cosmological and geographical conditions. These environmental factors are directly affecting the performance losses in solar cells. The presented paper attempted to use the long short-term memory (LSTM) to evaluate the environmental parameters influencing on photovoltaic cells performance losses. According to the simulations, intensity and radiation angle, shadow, temperature, wind and air pressure are the main parameters which affect the solar cells functions and loss the performance.

1. Introduction

In 1839, a French experimental physicist, Edmund Becquer discovered the creation of a weak electrical current when he put some material in front of the sun (Jieming et al., 2013). According to increasing of the global demand for electricity and imperious need to track the global challenges of global energy security, climate changes and sustainable development, a significant amount of research effort has been carried out on the development of Photovoltaic cells (PV), which are basically semiconductors that can directly convert light into electricity with PV effect. Solar energy which comes from the sun in the form of solar irradiance can be directly converted to electricity by using PV technology. PV technology uses solar cells made of semiconductors to absorb the irradiance from the sun and convert it to electrical energy (Jacobson et al., 2011). This energy is used in different ways; it's most important application is that it can be turned in to heat (such as CSP Solar heating cells) and electricity (such as PV solar panels). Solar heaters work through adsorption of solar energy and light radiation on adsorbent plates, and provide heating energy equivalent to optimal capacity (maximum absorption capacity in cells) for utilized installations (Sharma et al., 2012). The PV technology can be grouped into two categories: Silicone Crystal (C-Si) and Thin Factor (TF). The efficiency of converting PV units made from C-Si is around 13-20%, while the efficiency of PV units made from TF is around 6-12% (Seyed-mahmoudian et al., 2013). TF technologies use a small amount of active materials that can be produced at a lower cost than C-Si (Patel and Agarwal, 2008). Recently, many emerging technologies and new PVs such as centralized photovoltaics (CPV), organic solar cells, inorganic TFs, thermal photovoltaics (TPVs) are currently under investigation. PV markets are expanding in the line with the advancement of PV technologies (Soufi et al., 2017).

Solar panels are normally expected to be designed to produce the most ideal output or optimum yield. The factors that influence the determination of the ideal output or optimum yield can be classified into two categories as changeable variables and unchangeable variables. The variables that can be changed provide design flexibility to respond to varying installation requirements, while the variables that are unchangeable need to be adapted to by default. The various changeable and unchangeable variables influence the configuration and design of a solar panel, the installation and operation of a solar panel and play an important part in solar panel generation. However, as more and more PV power plants are built in the upper MW and GW power rangers in the future; there is a need for more attention to be paid to this problematic area which directly affects the efficiency of the power generation (Maghami et al., 2015).

There are numerous studies about photovoltaic performance variation related to environmental changes which present efficient and effective parameters like wind, temperature, air pressure, sun

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light intensity and radiation angle, shadow, snow, air pollution, irradiation, dust, volcano and climate. Thus, to ensure optimal efficiency and maximum energy yield, an in-depth investigation to analyse the effect of dust on solar panels is necessary. In addition to analysing the effects that stem from such issues, this paper presents the new algorithm based on long short-term memory (LSTM) methodology for predicting the environmental factors efficiency on PV performance.

2. Long short-term memory (LSTM)

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. Unlike standard feed-forward neural networks, LSTM has feed-back connections. It can not only process single data points, but also entire sequences of data. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. LSTMs were developed to deal with the exploding and vanishing gradient problems that can be encountered when training traditional RNNs. Relative insensitivity to gap length is an advantage of LSTM over RNNs, hidden Markov models and other sequence learning methods in numerous applications (Liu et al., 2017). The Fig. 1 shows the LSTM basic architecture.

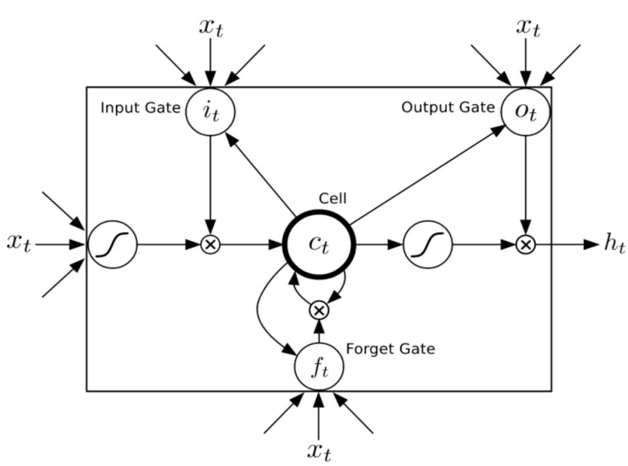

Figure 1. A view of LSTM architecture (Liu et al., 2017)

LSTM was proposed in 1997 by Sepp Hochreiter and Jürgen Schmidhuber (Hochreiter and Schmidhuber, 1997). By introducing Constant Error Carousel (CEC) units, LSTM deals with exploding and vanishing gradient problems. The initial version of LSTM is block included cells, input and output gates. In 1999, Felix Gers and his advisor Jürgen Schmidhuber and Fred Cummins introduced the forget gate (also called “keep gate”) into LSTM architecture enabling the LSTM to reset its own state (Greff et al., 2015). In 1999, Gers and his colleague added peephole connections (connections from the cell to the gates) into the architecture. Additionally, the output activation function was omitted (Gers et al., 1999). Cho et al. (2014) put forward a simplified variant called Gated recurrent unit (GRU). Among other successes, LSTM achieved record outcomes in the natural language text compression and unregimented connected handwriting recognition and won the ICDAR handwriting competition. LSTM networks were a major component of a network that achieved a record 17.7% phoneme error rate on the classic TIMIT natural speech dataset (Graves et al., 2013). Since 2016, LSTMs have been used by major technology companies including Google, Apple, and Microsoft as fundamental components in new products. For example, Google used LSTM for speech recognition on the smartphone, for the smart assistant Allo and for Google Translate. Apple uses LSTM for the "Quicktype" function on the iPhone and for Siri. Amazon applies LSTM for Amazon Alexa. In 2017, researchers from Michigan State University, IBM Research, and Cornell University published a study in the Knowledge Discovery and Data Mining (KDD) conference. Their study describes a novel neural network that is performed better on certain data sets than the widely used long short-term memory neural network (Baytas et al., 2017). Further in 2017 Microsoft reported reaching 95.1% recognition accuracy on the Switchboard corpus, incorporating a vocabulary of 165,000 words. The approach used "dialog session-based long-short-term memory" (Haridy, 2017).

In theory, classic RNNs can keep track of arbitrary long-term dependencies in the input sequences. The problem of vanilla RNNs is computational (or practical) in nature: when training a vanilla RNN using back-propagation, the gradients which are back-propagated can "vanish" (that is, they can tend to zero) or "explode" (that is, they can tend to infinity), because of the computations involved in the process, which use finite-precision numbers. RNNs applying LSTM units partially solve the vanishing gradient problem, since LSTM units also allow gradients to flow unchanged. However, LSTM networks may still suffer from the exploding gradient problem (Kelleher, 2018). The LSTM unit from RNNs is presented in Fig. 2. As seen in this figure, the LSTM is used the recurrent neural network to use the prediction and learning.

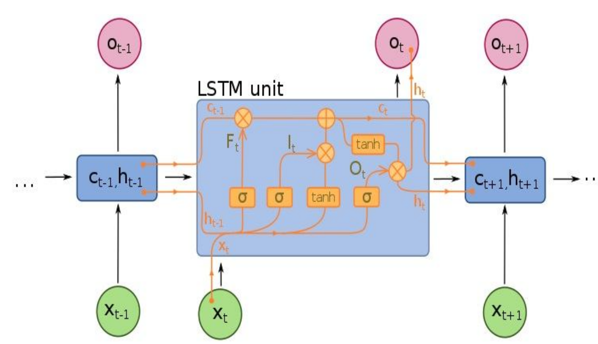

Figure 2. A view of LSTM unit in RNNs (Kelleher, 2018)

3. Material and Methods

Producing the electricity by solar panels can be seen as an energy generator to answer the future needs. The solar panels can do this without creating much noise, toxic gases or greenhouse gases (Hernandez et al., 2014). In this subject the goal can be considered as maximizing the energy output of a given panel device. However, due to the different environmental conditions impact on power output of a typical PV cell or module (Tajuddin et al., 2013). The present study uses the LSTM algorithm for prediction and classification of effect of environmental parameters on photovoltaic performance and power losing. To this end, the main environmental parameters related to PV cells are gathered and entered in LSTM based learning algorithm. The proposed model is implemented on a large dataset of solar cell parameters with 18 layers consisting of random elimination layers, dense layer, LSTM layer and fully connected layer. The dataset contains over 2 million rows in 22 columns. The implementation language is Python 3. In order to compare the proposed model of LSTM deep neural network with 10 other algorithms in terms of accuracy, accuracy, readability and f1 are compared. Figures 3 and 4 are presented the flowcharts of processing layouts of utilized methodology.

In machine learning and specifically the problem of statistical classification, a confusion matrix (known as an error matrix) is used to evaluate capability and specified layout that allows performance visualization of a supervised learning algorithm. It is a special kind of contingency table, with two dimensions ("actual" and "predicted"), and identical sets of "classes" in both dimensions (each combination of dimension and class is a variable in the contingency table) which is illustrated in Fig. 5. This table of confusion is applied to estimate the number of false positives, false negatives, true positives, and true negatives which allows more detailed analysis than mere proportion of correct classifications or analyses accuracy. Accuracy is not a reliable metric for the real performance of a classifier, because it will yield misleading results if the data set is unbalanced. So, the matrix is present the recognition rate as precision, recall and f1-score were named as relevant documents (Eq. 1 to 4).

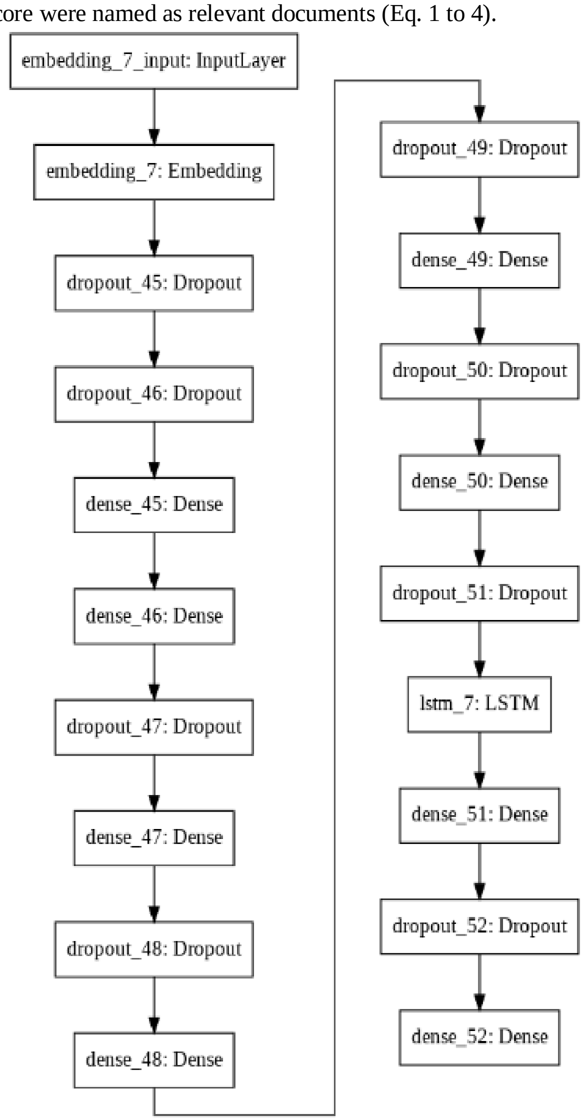

Figure 3. Proposed model flowchart

Layer (type)	Output Shape	Param #
embedding_7 (Embedding)	(None, 12, 5)	1500
dropout_45 (Dropout)	(None, 12, 5)	0
dropout_46 (Dropout)	(None, 12, 5)	0
dense_45 (Dense)	(None, 12, 200)	1200
dense_46 (Dense)	(None, 12, 100)	20100
dropout_47 (Dropout)	(None, 12, 100)	0
dense_47 (Dense)	(None, 12, 100)	10100
dropout_48 (Dropout)	(None, 12, 100)	0
dense_48 (Dense)	(None, 12, 100)	10100
dropout_49 (Dropout)	(None, 12, 100)	0
dense_49 (Dense)	(None, 12, 400)	40400
dropout_50 (Dropout)	(None, 12, 400)	0
dense_50 (Dense)	(None, 12, 100)	40100
dropout_51 (Dropout)	(None, 12, 100)	0
lstm_7 (LSTM)	(None, 100)	80400
dense_51 (Dense)	(None, 100)	10100
dropout_52 (Dropout)	(None, 100)	0
dense_52 (Dense)	(None, 1)	101

Figure 4. Proposed model layout flowchart for parameter prediction

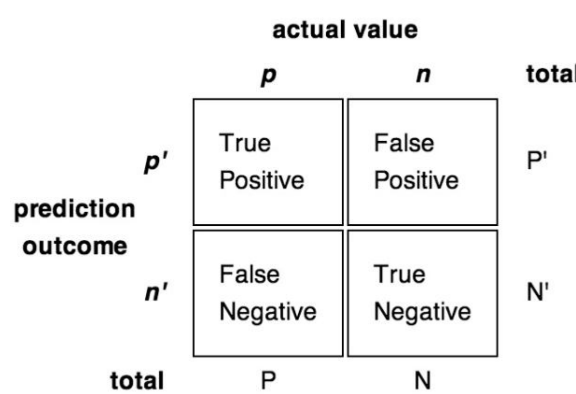

Figure 5. The confusion table

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{f1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

These relationships are used in this study to evaluate the algorithm efficiency and capability for assessment of the prediction of environmental factors on PV performance. Also, for justification of used LSTM-based method, such standard machine learning methods as support vector machine (SVM), k-nearest neighbors (k-NN), decision tree, logistic regression, naïve-bayes classifiers, multilayer perceptron (MLP), extra tree, random forest and stochastic gradient descent (SGD) are applied. The result of the used algorithm is compared with the mentioned methods and the evaluated relevant documents of confusion matrix are considered as the factors of efficiency and capability assessment or evaluation criteria.

4. Results and discussions

The results of the algorithm Implementation is presented in Figs 6 to 9. According to these figures the sun light intensity and radiation angle, air temperature, air pressure, wind speed and direction are the main factors influencing on solar panels performance which are considered and presented by many scholars in various reports. In order to evaluate the capability of used algorithm the loss function of the model is measured. So it is shown in Fig. 10. As seen in this figure the estimated loss amount is reduced significantly by increasing the learned layers.

	count	mean	std	min	25%	50%	75%	max
Year	2277830.0	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DOY	2277830.0	2012.25	1.49	2010.00	2011.00	2012.00	2014.00	2015.00
PST	2277830.0	189.94	105.15	1.00	97.00	191.00	280.00	366.00
GHI	2277830.0	1180.48	692.16	0.00	600.00	1201.00	1800.00	2359.00
DNI	2277830.0	217.06	306.46	0.00	0.00	3.01	410.27	1494.38
DHI	2277830.0	238.88	357.05	0.00	0.00	0.00	599.66	4504.32
Air Temp	2277830.0	70.75	112.80	0.00	0.00	2.96	100.61	915.32
Pressure	2277830.0	17.06	4.20	2.66	14.31	17.00	19.71	38.50
Wind Speed	2277830.0	1010.25	1.33	999.00	1010.00	1010.00	1010.00	1024.00
Wind Dir	2277830.0	1.72	1.17	0.00	0.88	1.59	2.46	11.40
Wind Dir STD	2277830.0	145.99	94.91	0.00	53.69	176.90	212.00	360.00
Wind Speed STD	2277830.0	25.23	20.19	0.00	10.05	19.37	38.00	103.70
Wind Speed Peak	2277830.0	0.35	0.24	0.00	0.18	0.29	0.47	2.92
Global Uncorrected	2277830.0	2.38	1.60	0.00	1.08	2.14	3.48	17.86
Direct Uncorrected	2277830.0	217.61	307.46	0.00	0.00	4.05	410.29	1478.84
Diffuse Uncorrected	2277830.0	254.50	375.62	0.00	0.00	0.00	648.08	6257.49
Zenith	2277830.0	398.19	423.26	0.00	0.00	0.00	882.00	1011.00
Azimuth	2277830.0	89.72	39.12	10.53	57.77	89.30	121.80	169.50
Humidity	2277830.0	13.02	0.55	0.00	12.69	12.86	13.33	14.45
Precipitation	2277830.0	75.61	19.55	4.96	67.10	79.75	90.60	100.00

Figure 6. Solar cell data set and impact environmental parameters

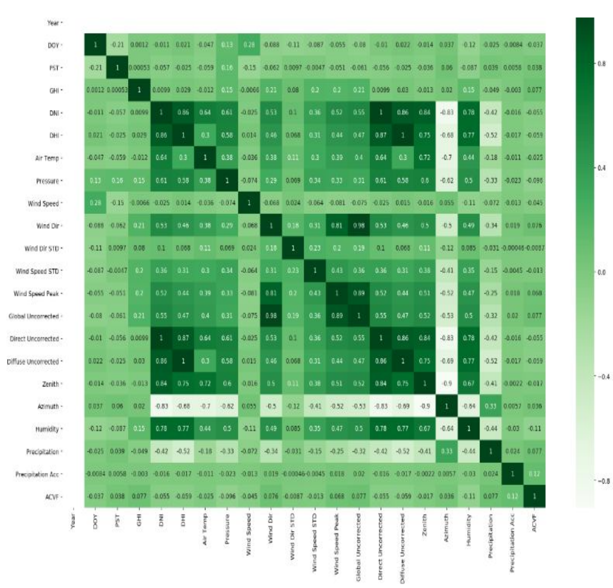

Figure 7. Correlation coefficient of data set attributes

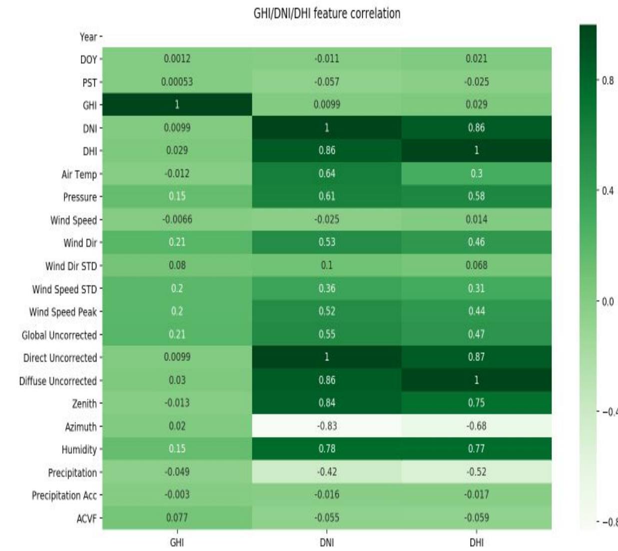

Figure 8. Correlation of GHI, DNI, DHI to other environmental parameters

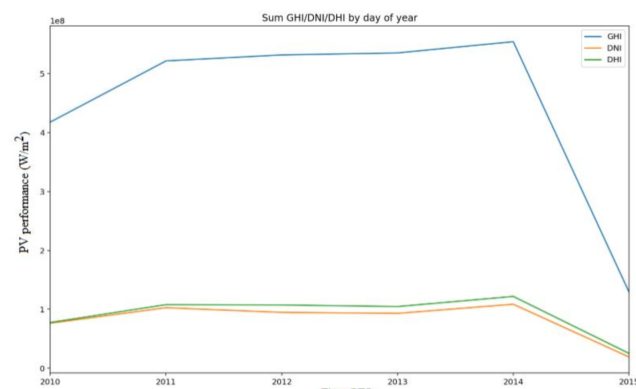

Figure 9. Main emission characteristics on PV

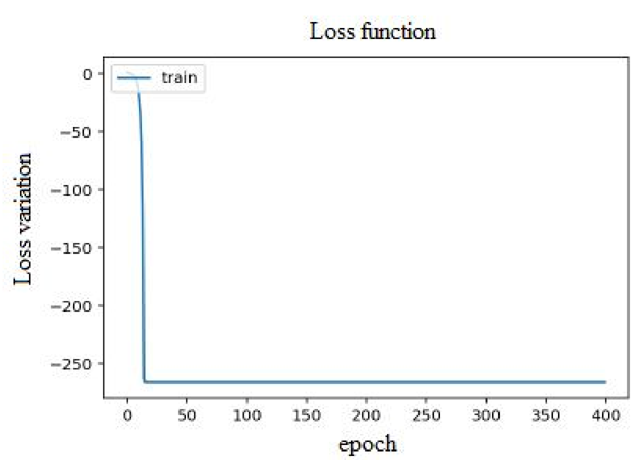

Figure 10. The estimated loss function of model

The figures 11and12 present the justification of the used algorithm results by standard machine learning methodologies. According to the obtained results, the proposed algorithm based on LSTM shows higher efficiency and capability than other methods which estimated confusion matrix as accuracy as 96.70, precision as 95.00, recall as 100 and f1-score as 74.21. In this study, the presented method estimated higher score than other methods. So that the results show significant difference compared to the justification methods.

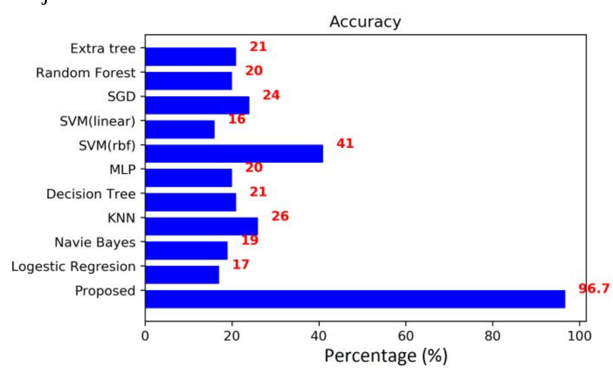

Figure 11. Evaluation of the accuracy of the proposed method and other ones

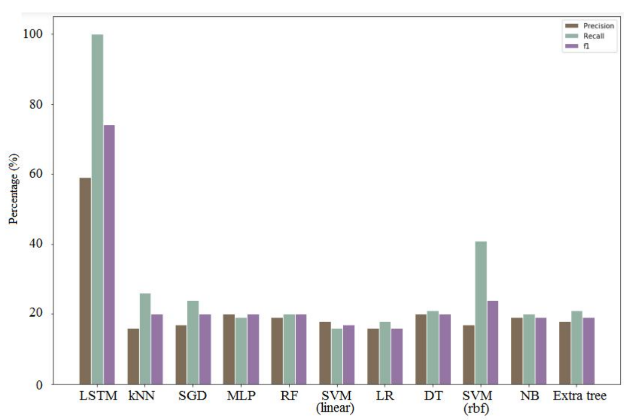

Figure 12. Evaluation of the criteria of the proposed method and other ones

5. Conclusion

Many factors determine the ideal output or optimum yield in a photovoltaic module. The environment is one of the contributing factors which directly influences on photovoltaic performance. This paper has investigated the environmental parameters involved in reduction of the photovoltaic (PV) module performance which is affected by solar energy transformation capability. To this end, long short-term memory (LSTM) based algorithm is used for prediction and classification of high impact environmental factors related to the power output and performance losses in solar cells. According to the simulation results, sun light intensity and radiation angle, air temperature, air pressure, wind speed and direction are the main factors influencing on solar panels performance. For the justification of the used LSTM-based method, such standard machine learning methods as support vector machine (SVM), k-nearest neighbors (k-NN), decision tree, logistic regression, naïve-bayes classifiers, multilayer perceptron (MLP), extra tree, random forest and stochastic gradient descent (SGD). The result of the used algorithm is compared with the mentioned methods and the evaluated relevant documents of confusion matrix are considered as factors of efficiency and capability assessment or evaluation criteria. Based on achievement of justifications the proposed algorithm based on LSTM shows higher efficiency and capability than other methods which estimated confusion matrix as accuracy as 96.70, precision as 95.00, recall as 100 and f1-score as 74.21 which are show significant difference compared to the justification methods.

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