INTEGRATING IOT DEVICES AND DEEP LEARNING FOR RENEWABLE ENERGY IN BIG DATA SYSTEM

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Renewable energy use has increased rapidly in recent years. As a result, it has attracted many researchers and industries to provide safe and sustainable energy to customers. However, the high use of renewable energy has caused many problems in its forecasts. To provide energy forecasts, data was collected from wind turbines or solar panels. Several approaches have been proposed for renewable energy forecasting, but they do not take into account Big data characteristics. These approaches focus only on data analysis and are limited. This paper proposes an ideal architecture that integrates IoT technology, Big Data system and Deep Learning paradigm for energy forecasting. The proposed architecture is divided into four layers: renewable energy layer, Big Data layer, IoT layer and Deep Learning layer. Renewable energy data are Big, thus a Big data layer is proposed for the storage and processing of renewable energy data. Then, the Deep Learning layer is used to predict renewable energy. A distributed LSTM algorithm is implemented and compared with three different models to illustrate the predictability and optimization of execution time in the proposed system. Finally, IoT technology is used to facilitate the acquisition of weather, wind or solar data.

Keywords: Deep learning, Big data, Internet of things, Distributed long short term memory.

1. Introduction

The use of renewable energy resources is increasing rapidly worldwide. In 2017, renewable energy consummation represented up to 17% of total global energy consumption. Moreover, these renewable resources can provide 8% of the world's energy[1].

Several researchers have proposed to use Smart Grid for renewable energy [2, 3, 4]. Smart Grid describes the system that can manage information and communication technologies in electricity systems [5, 6, 7]. One of the most important advantages of the Smart Grid system is the flexibility to use its

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information to make the best decision [2]. Smart Grid uses the information collected from solar panel or wind turbine. An additional important information about the weather state is, for example, the temperature degree or even wind speed. Smart Grid is widely used in data sensing transmission and processing. Therefore, the Internet of Things technologies play an important role in Smart Grid construction. IoT technologies assure the communication between users and Smart Grid devices; they allow real-time interaction in the system. Yun M. et al.[8]. classified the functionalities of IoT in Smart Grid as follows:

- Monitoring the state of equipment,
- Collect information from equipment,
- Control Smart Grid with the application interface.

IoT data is increasing and its volume is estimated per Terabyte or Petabyte. Smart Grid data is especially characterized by velocity, because the data generation speed is in real time. The dimensions and format of sensor data in Smart Grid have a variety of structures. This work considered smart energy data as very big, with its characteristic volume, variety and velocity. This consideration is justified by the lack of studies in this orientation, which consider renewable energy data as Big Data. Several authors proposed only the renewable energy forecasting. The authors do not take into account the Big Data's problems. Therefore, their proposed models still need to be improved.

IoT sensor in smart energy collects large amounts of time series data. This data is analyzed with multiple models, a statical model such as ARIMA Model, GARCH Model [9].or simple machine learning models such as Support Vector Machine, linear regression k-means, etc. Although these models have given good results, they are limited.

The Deep Learning model is introduced to analyze the time series. The LSTM network (Long-Short Term Memory) becomes a good Deep Learning model to process and predict important events with long intervals and delays in the time series. LSTM kernel is used to forecast renewable energy in Big Data. The integration of Big Data for renewable energy forecasting is a challenge in various fields, including data storage, monitoring and analysis. Thus, this work aims to address the following questions:

- What is the system that can treat very large amounts of stored, selected and processed data?
- What is the model that can analyze these very large amounts of data collected from the IoT?

The reminder of the paper is organized as follows: Section 2 describes the state of the art for renewable energy forecasting. Section 3 presents the proposed approach, which is based on IoT devices and Deep Learning. Then, in Section 4, the validation of the proposed system is presented. Finally, Section 5 draws conclusions and provides some suggestions for future work.

2. Related works

Our work is related to Smart Grid which includes IoT, big data system, Machine learning for renewable energy and Smart grid management and integration .

2.1. Machine learning for Renewable energy

Several researchers have proposed machine learning approaches for renewable energy. Aka et al. [10] proposed two Machine Learning approaches for Short-Term Wind Speed Time-Series prediction, which are extreme learning machines and multi-objective genetic algorithms combined with the nearest neighbors approach for estimating prediction intervals of wind speed.
Wenbin et al. [11] proposed a data mining approach consisting of k-means and artificial neuronal network for wind energy. K-means algorithm is used for clustering days into categories. Then, the authors used a bagging algorithm-based neural network to predict wind energy.
Ren et al.[12]presented a model for wind energy forecasting. The authors integrated empirical mode decomposition with support vector machine.
Yang et al.[13] proposed a nonparametric approach for short-term probabilistic wind generation forecast based on the sparse Bayesian classification and Dempster-Shafer theory.
In [14], the authors presented Stacked auto-encoder and Stacked denoising auto-encoder neural networks are for ultrashort-term and short term wind speed forecasting.
In [15], the authors proposed a method integrate discrete wavelet transform, Auto-Regressive Moving Average and Recurrent Neural Networks.
Hao et al. [16, 17] presented a survey machine learning approach for predicting and optimizing the solar water heater. The authors studied several models such as Super Vector Machine, extreme learning machine and artificial neural networks and developed a software to assist the quick perdition. Hao et al.[18] proposed machine learning for the intrinsic trends of $CO2$ solubility in blended solutions. The authors applied a general regression neural network (GRNN) as the algorithm.

2.2. Deep learning approach

Deep learning has been very successful in many machine learning applications, such as image analysis, text mining or speech recognition. It is composed of multi-level representations and features in hierarchical architectures. The Deep Learning algorithm can be applied to classification and regression problems. Various Deep Learning models have been presented, such convolutional neural network, stacked auto-encoder, deep belief network and recurrent neural network.

- Convolutional neural network: They are composed of three layers, convolutional layer, pooling layer, and fully-connected layer [19].

- Stacked auto-encoder:composed of stacking several auto-encoders. It has two stage encoding stage and decoding stage[20].
- Deep belief network: Stacked-up several restricted Boltzmann machines. It is composed of visible and hidden layers[21].
- Recurrent neural network: is suitable to time series data problems. It learns the features of the series data from a memory in previous inputs[22].

2.**2**.1. *Deep learning for energy forecasting.* Rodrigo et al. [23] used deep learning approach to analyze data of monthly consumption of Brazilian power company.The author evaluated the system with three algorithms, fully connected, convolution neuronal network and long term short memory. Amarasinghe et al.[24] proposed a convolution neuronal network to perform energy load forecasting at the individual building level. The authors validated their work with benchmark data set of electricity consumption for a single residential customer. He [25] proposed a deep learning algorithm for short term load forecasting,the author used convolution neuronal network to extract feature and recurrent neuronal network to model the implicit dynamics. He validated the proposed model by hourly load values of a city in North China. Kuo [26]proposed deep convolution neuronal networks for energy forecasting. Its convolution neuronal networks are composed of six layers, three Convolutions, and three Pooling. In experimentation, the auther used data from the coastal area of the USA. Yubo et al. [27] proposed a deep belief network to predict wind power. The authors compared the proposed model with multilayer perception and Support vectors machine. Deep belief network can learn the variation of wind power and improve accuracy. Huai et al.[21] proposed deep learning approach based for probabilistic wind power forecasting. The proposed model is based on wavelet transformation and convolutional neural network. The authors applied the proposed model on wind farm from China. This model provides a better understanding of the uncertainties in wind energy data. Wan et al.[28] proposed a deep feature learning (DFL) approach to wind speed forecasting due to its advantages at both multi-layer feature extraction and unsupervised learning. A deep belief network (DBN) model for regression with an architecture of 144 input and 144 output nodes was constructed using a restricted Boltzmann machine (RBM). The authors compared the model with single hidden layer neural networks, with three hidden layers and support vector machine. The proposed model can learn effectively the complex feature of wind speed and improves its prediction.

2.**3**. Smart Grid energy integration and management

In [29]Proposed smart Grid energy management system based control mechanism for electricity demand. They present a power distributed scheduling protocol to optimize electricity consumption. In [30] proposed smart grid integration of renewable sources and improvement of power quality. Authors discussed the impact of the integration of renewable energy source on power quality indices includes distribution system operator, high voltage,low voltage, medium voltage, point of common coupling,supervisory control and data acquisition and transmission system operator.

3. Proposition

This section presents the proposed approach. Firstly, an architecture, based on multi-layers (Internet of Things, Deep Learning model and Big Data system) to facilitate the integration of renewable energy, is described. Then, an extended data mining process for the renewable energy system is proposed. Finally, the distributed Long Short Term Memory is suggested as a deep learning algorithm for the proposed system.

3.1. Multi-Layer Architecture

Our architecture is composed of four layers: renewable energy layer, IoT layer, deep learning layer, and big data system layer.

- Renewable energy layer: provides essentially the renewable energy power like wind or solar energy to other layers which need the energy to work. In general, it is responsible for all issues concerning renewable energy.
- Internet of Things layer: concerns the Internet of Things devices, the circuit driver and the program configuration.
- Big Data layer: involves the Big Data system, as data storing and processing.
- Deep Learning layer: is the complementary layer of the proposed system. It can analyze data gathered from IoT layer. The main objective of this layer is to predict or describe renewable energy data. Figure 1.represents the different layers of the proposed system.

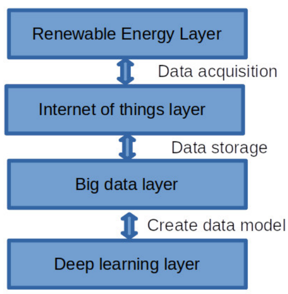

Fig. 1. Layers of the proposed system

The Internet of Things layer captures data from renewable energy layer. This data includes the characteristics of energy generating devices as well as all factors affecting power generation such as weather, temperature and wind speed. The Big Data system stores data gathered from Internet of Things layer in $Data_1$,$Data_2$, ...$Data_n$ .Each $Data_i$ is assigned to $Node_i$. Data stores data in HADOOP FILE SYSTEM (HDFS) format. The size of File in HDFS is measured by gigabyte or a terabyte. HDFS adopts large scale distributed files. The user of the proposed architecture can capture data distributed geographically from solar stations or wind farms and store it in HDFS data files. Deep Learning layer consists of Deep Learning algorithms,Deep $learning_1$,Deep $learning_2$...Deep $learning_n$. Each Deep learning $model_i$ use data of node $Datanode_i$ in training,to create $Model_i$. The created $Model_i$ is used to predict energy forecasting. Figure. 2 represents the architecture of the proposed system.

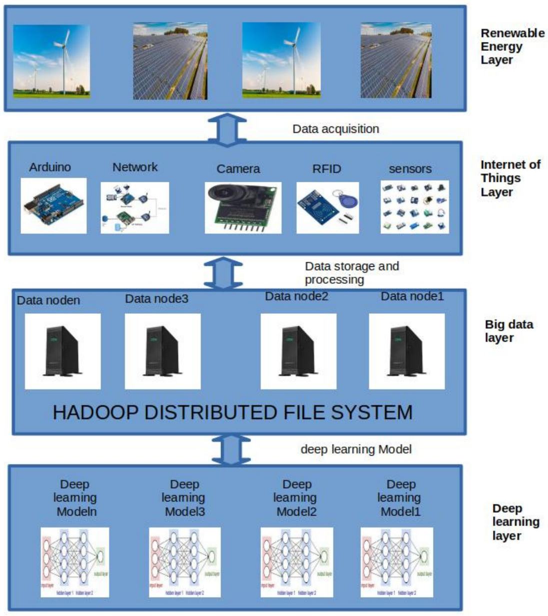

Fig. 2. Architecture of the proposed system

3.**1**.1. *Data mining process for renewable energy.* The data mining process implies multiple steps, which are followed by the system developers for its implementation. The cross-industry standard process for data mining called CRISP-DM [31] is a standardization for data mining process. This study proposed an extended CRISP-DM process which takes into consideration renewable energy. This process enables developers to implement renewable energy software easily, as well as display the source of energy. The proposed extended data mining process is based on:

- Understanding and determination of the objective of the proposed system.
- Data acquisition: IoT captures data to obtain input data in the next steps.

- Modeling the system: In this step, the Deep Learning algorithm is used to analyze data.
- Evaluation: The created model is evaluated to validate its usability.
- Deployment: After the validation of the proposed system, it can be used by customers. Figure 3 represents the extended data mining process for renewable energy.

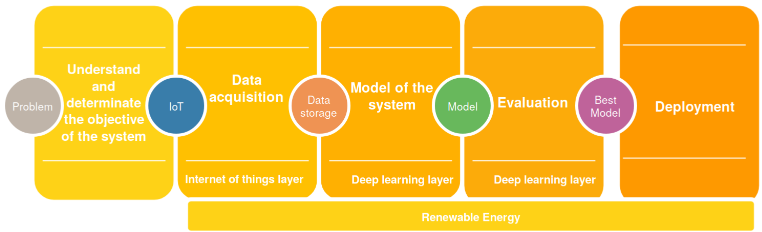

Fig. 3. Extended data mining process for Renewable energy

3.2. Distributed and parallel Deep learning model

Subsequently, an architecture based on Deep Learning is proposed to execute tasks in distributed and parallel mode. The training data of the Deep Learning model is distributed over the Datanode. Therefore, it can build models for each Datanode in parallel.

3.2.1. *Distributed and parallel Long Short Term Memory Algorithm.* A distributed and parallel LSTM Deep Learning algorithm is proposed for renewable energy forecasting. This algorithm has the same kernel of LSTM algorithm. LSTM network is a type of recurrent networks. It is introduced to treat the problem that has a time dimension, in which Recurrent Neuronal Networks (RNN) cannot track the relationship across a long time. It is specifically proposed to learn long term dependencies and able to resolve vanishing and exploding problems, which can exist in a recurrent neural network[32].By adding a set of memory units to recurrent neural networks, LSTM effectively solves the vanished gradient problem or gradient explosion. Figure 4 represents the LSTM structure.

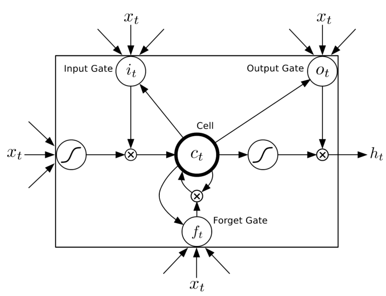

Fig. 4. LSTM structure [33, 34]

The LSTM is composed of three gates for each unit, namely forget gate, input gate and the output gate. Memory cell records all historical information in the current time from the three gates forget gate(f_t), input gate (i_t), and the output gates (o_t). The gates take their values in the interval[0..1].

The forget gate (f_t), input gate (i_t) and output gate (o_t), are expressed as follows:

$$f_t : \text{Forgate gate activation:} \quad f_t{=}\sigma_g(W_f x_t + U_f h_{t-1} + b_f) \tag{1}$$

$$i_t : \text{Input gate activation:} \quad i_t{=}\sigma_g(W_i x_t + U_i h_{t-1} + bi) \tag{2}$$

$$o_t : \text{Output vector of LSTM:} \quad o_t{=}\sigma_g(W_o x_t + U_o h_{t-1} + b_o) \tag{3}$$

Where, f_t t is the forget gate activation, i_t is the input gate activation and o_t is the output vector of LSTM. The full data of the proposed system is distributed; each $Data_i$ is stored in $Node_i$. LSTM algorithm is applied for each $Datanode_i$, as follows:

Algorithm 3.1. *Set of Nodes* $=\{Node_1, Node_2, ..., Node_n\}$ *of Node, Set of Data store in Nodes* $= \{Node_1(Data_1),\ Node_2(Dat_2), ..., Node_n(Data_n)\}$ *of* $DataNode_i$

Set of Model Model$=\{Model_1,\ Model_2,...,Model_n$ *of Model*$\}$

For Each($Node_i(datanode_i)$*)*

$Model_i \leftarrow Node_i(LSTM(Datanode_i))$ *Return* $Model_i$

4. Validation and experimentation

Hadoop Distributed system and SPARK framework were used to validate the proposed approach. Then, LSTM algorithms were implemented using python. Data was also used for the evaluation step, which contained time series data for power system modeling, namely wind and solar power generation from two countries: Austria and the Netherlands. The different components of the proposed system are described as follows:

- **HADOOP:** As we mentioned in section 3.**1**, it can support the distributed file system. In the case of the capacity of storage outgrows of a single machine, it needs to divide the storage on separated machines.The file system which manages the storage across a network is called distributed file system [35].
- **Spark:** It is an open source distributed programming. It provides great performance advantages on Hadoop, it can accelerate tasks execution [36].
- **Data description:**:The data of two countries, namely Austria and the Netherlands was used, which contains information about renewable energy solar and wind energy in the hourly resolution[37] The hourly weather data[38] of the two countries were also used in the experimentation. In

addition, important information that can be collected from the sensors. Data was divided into two nodes. The attributes of each data node are:

- Node1 of Austria
  - utc_timestamp : Start of time period in Universal Time.
  - AT_Solar generation actual : Actual solar generation in MW.
  - AT_Wind onshore generation actual : Actual wind onshore generation in MW.
  - AT_windspeed10m : Wind speed weather variable in m/s.
  - AT_temperature : Temperature weather variable in degrees C.
- Node2 of Netherlands
  - utc_timestamp :Start of time period in Universal Time.
  - NL_solar_generation_actual Actual :Solar generation in MW.
  - NL_wind_offshore_generation_actual: Actual wind offshore generation in MW.
  - NL_windspeed_10m: Wind speed weather variable in m/s.
  - NL_temperature :Temperature weather variable in degrees C.

- **Development of LSTM algorithm:** algorithm was developed using python. sciPy environment was used with Keras Deep Learning library. LSTM network has an input, 04 hidden neurons and one output layer return the prediction value. Hyperparameters are the active function sigmoid, batch s ize 1 and it is trained on 10 epochs. The train size is 5885 and the test size is 2899. The training converges after 10 epochs. The proposed model converges with Adam optimization algorithm. This algorithm is an extension to stochastic gradient descent. Adam combines the advantages of Root Mean Square Propagation (RMSprop) and Adaptive Gradient Algorithm (AdaGrad). It uses the squared gradients to scale the learning rate like RMSprop and moving average as AdaGrad for momentum [39].
- **Description of the system functionality according to the proposed architecture:** A multi-layer architecture for renewable energy architecture was proposed. The first layer is responsible of renewable energy of solar panel farms and wind turbines in Austria and the Netherlands. The second layer is the Internet of Things layer. This layer provides the Internet of Things protocol, peripheral and network communication to capture data, which is provided by the renewable energy layer, such as temperature, wind speed, etc. The Big Data layer stores data collected from the previous layers. The proposed model has two data nodes, the first for Austria and the second for the Netherlands. The Deep Learning layer is trained on Austria $datanode1$ and the Netherlands $datanode2$ to create a model that can describe the energy generation of Austria $datanode1$ and energy generation of the Netherlands $Datanode2$. Figure. 5 represents the Hadoop data node of renewable energy and weather data for Austria.

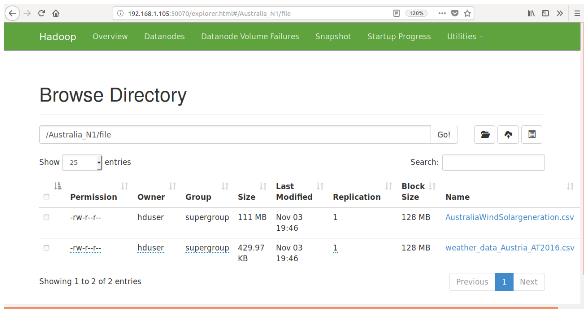

Fig. 5. Hadoop node1 for Austria renewable energy and weather data

Node1 results: Figure. 6, shows the real values of wind generation in Austria and the results of the wind distributed LSTM power prediction in Austria. It can be noted that the output layer predicts either the wind generation or the solar generation. Also, data from Austria and the Netherlands data is used to trained on Distributed LSTM networks, each LSTM networks trained on separate Dataset (Austria or the Netherlands). The real data is drawn with blue and the predicted LSTM model with orange or green.

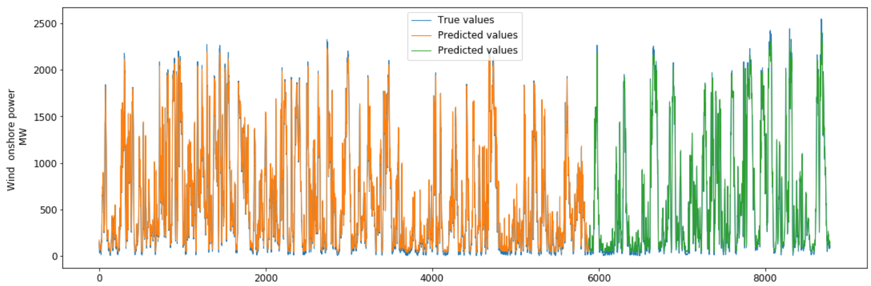

Fig. 6. LSTM Wind power prediction

Figure .7, presents the real values of solar power in Austria and the results of the proposed distributed LSTM prediction for solar data in Austria. The real data is drawn with blue and the predicted LSTM model with orange or green.

Node2 results: Figure. 8 indicates the real values of wind generation of the Netherlands and the results of the proposed distributed LSTM power prediction for the wind in the Netherlands. The real data is drawn with blue and the predicted LSTM model with orange or green.

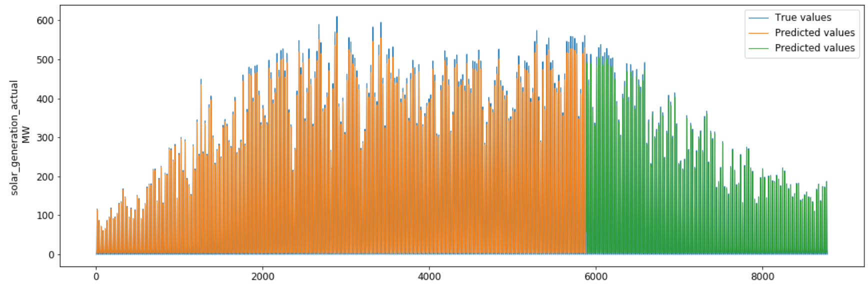

Fig. 7. LSTM solar power prediction

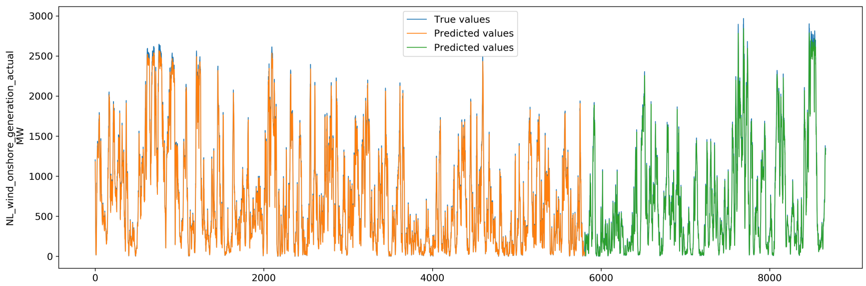

Fig. 8. LSTM Wind power prediction

Figure 9 shows the real values of solar power in the Netherlands and the results of the proposed distributed LSTM prediction for solar in the Netherlands. The real data is drawn with blue and the predicted LSTM model with orange or green.

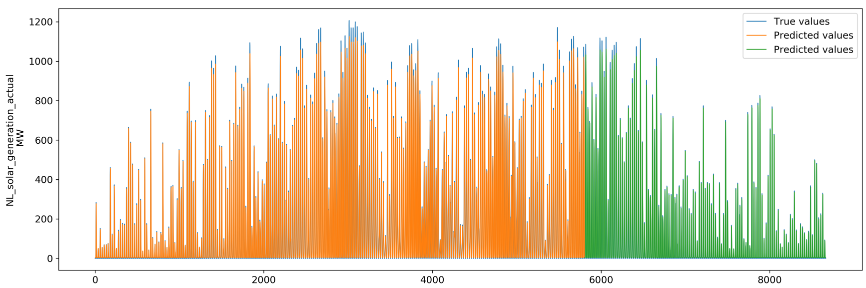

Fig. 9. LSTM solar power prediction

Comparison with machine learning models: To evaluate the outperform of the proposed model, it was compared with other machine learning algorithms, like Linear Regression (LR), Discriminant Analysis (DA) and Super

Vector Machine (SVM). Each model was evaluated using Mean Square Error (MSE) and Root Mean Square Error (RMSE). The Mean Square Error is the easiest metric for machine learning model evaluation. It gives a rough idea of the extent of the error. The loss function calculates the error between the real values and the predicted values y'. Root Mean Square Error (RMSE) is the square root of MSE, that scales the error to be the same of magnitude as the quantity being predicted[40]. and it can be written as follow:

$$MSE = \frac{\sum_{i=1}^{i=N} \left|y_i - y'_i\right|^2}{N} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} \left|y_i - y'_i\right|^2}{N}} \tag{5}$$

Tables 1, 2, 3,and 4 summarize the results obtained:

Table 1

Node2 Netherlands Wind energy forecasting

Error	LR	LDA	SVM	LSTM
MSE	186639.30	94269.10	123189.26	13717.09
RMSE	432.01	307.32	350.98	117.32

Table 2

Node1 Austria Wind energy forecasting

Error	LR	LDA	SVM	LSTM
MSE	69450.91	224622.47	114655.53	17009.37
RMSE	263.53	473.93	338.60	130.42

Table 3

Node1 Austria solar energy forecasting

Error	LR	LDA	SVM	LSTM
MSE	5739.28	2612.16	33616.04	2261.95
RMSE	75.75	51.10	183.34	47.56

Table 4

Node2 Netherlands Solar energy forecasting

Error	LR	LDA	SVM	LSTM
MSE	18847.16	20969.86	105402.77	7308.54
RMSE	127.38	144.80	324.65	85.49

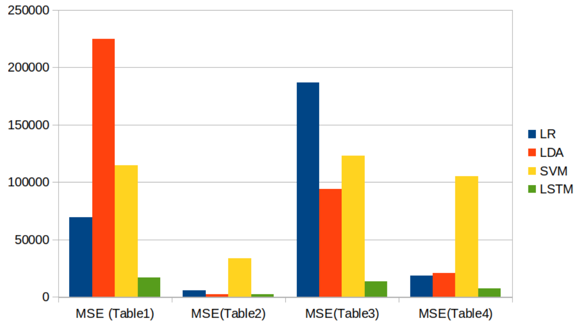

Fig. 10. Mean square error results

Figure.10 indicates that the Mean Square Error of LSTM model is the minimum for wind energy forecasting($Node1$ for Austria Wind energy forecasting and $Node2$ Netherlands Wind energy forecasting) and for solar energy forecasting ($Node1$ for Austria solar energy forecasting and $Node2$ Netherlands Solar energy forecasting). The other models register different values, for example, the error of the LDA model in Table 1 ($Node2$ for Netherlands Wind energy forecasting) is smaller than LR and SVM. But, the LR model has the minimum error in Table 2 ($Node1$ for Austria Wind energy forecasting) compared to LDA and SVM.

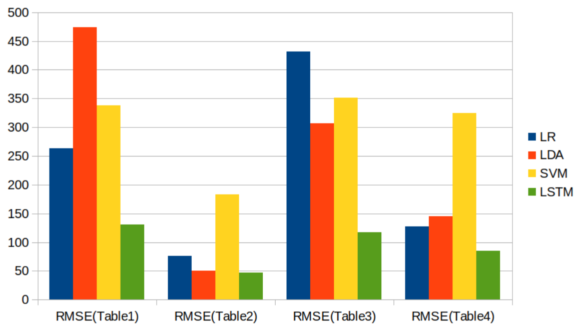

Fig. 11. Root mean square error results

Figure 11 indicates that the Root Mean Square Error of LSTM model is smaller of all nodes for wind ($Node1$ Austria Wind energy forecasting and $Node2$ Netherlands Wind energy forecasting) and solar ($Node1$ for Austria solar energy forecasting and $Node2$ for Netherlands Solar energy forecasting).

As a result, the Mean Square Error (Figure.10) and Root mean square error (Figure 11)demonstrate that the LSTM model is a better model than the other models available in literature (LR, LDA and SVM). The errors of the LSTM model are the minimum for wind and solar energy.

The performance of our system: The execution time was calculated to measure the performance of the proposed system. In addition, in the proposed distributed LSTM algorithm, data is distributed in multiple nodes. In each $LSTM_i$, the algorithm is executed in parallel, in $Node_i$. Therefore, the time of each executed task is reduced. Our model can predict the power generation, therefore it can predict the peak of power demand.It can optimize the power consumption due to possibility of reduce the unnecessary demand of power by the prediction of the power patterns' trends.

5. Conclusion and future works

This study proposed an architecture combined with renewable energy, Internet of Things, Deep Learning models and Big Data. The renewable energy layer was used for the generation of energy. Then, the Internet of Things layer was used to acquire data related to renewable energy generation such as wind speed and temperature. In Deep Learning layer, a distributed Long Term Short Memory algorithm was proposed. For Big Data system, two nodes under Hadoop Framework were used. The first one is the node for Austria renewable energy and the second one is the node for Netherlands renewable energy. The proposed distributed LSTM algorithm was compared with three machines learning algorithms, namely Linear regression, Linear discriminant and Super vector machine, to demonstrate its outperform. The results demonstrate that the predictive power of the proposed distributed LSTM algorithm are the best compared to those available in literature. On the other hand, the execution time the proposed distributed LSTM algorithm is optimized compared with other models which are not distributed. Based on the good results obtained in this study, for future work, the prediction of distributed LSTM algorithms can be improved and compared with other learning machines.

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