Modeling renewable energy production and CO_2 emissions in the region of Adrar in Algeria using LSTM neural networks

Seif Eddine Bouziane
Laboratoire de Gestion Electronique de Documents, Department of Computer Science, University Badji Mokhtar, PO-Box 12, 23000, Annaba, Algeria.
bouziane@labged.net

Julie Dugdale
University Grenoble Alps, Laboratoire d'Informatique de Grenoble (UMR 5217), Bâtiment IMAG 700 avenue Centrale, Domaine Universitaire - 38401 St Martin d'Hères.
julie.dugdale@imag.fr

Mohamed Tarek Khadir
Laboratoire de Gestion Electronique de Documents, Department of Computer Science, University Badji Mokhtar, PO-Box 12, 23000, Annaba, Algeria.
khadir@labged.net

Abstract

This paper addresses the slow-onset crisis of global warming caused by CO_2 emissions. Although electrical load is a major influence in a country's growth and development, it is also one of largest sources of greenhouse gases (GHG), CO_2 in particular. Therefore, switching to cleaner energy sources is a clear objective and forecasting electricity load and its environmental cost is a necessary task for electrical energy planning and management. This paper addresses short-term load forecasting of renewable energy (RE) production in the region of Adrar in Algeria with Adrar's photovoltaic (PV) farm and Kabertene's wind farm. The forecast is compared to the overall load demand, and the reduced amount of CO_2 resulting from using renewable energy instead of fossil fuels is calculated. The forecasting models use Long short-term memory (LSTM) neural networks, which were trained and validated using real data provided by the national state-owned company SONALGAZ. The results show good performance for the forecasting models with PV and wind models achieving a Mean-absolute-error (MAE) of 0.024 and 0.1 respectively. This RE can help to reduce CO_2 emissions by up to 25% per hour.

Keywords: Neural networks, Renewable energy, short-term forecasting, Carbon dioxide.

1. Introduction

Energy is undoubtedly a fundamental element in our lives due to its increased use in several domestic and industrial contexts. This prompts us to consider new techniques for producing energy.

Algeria is a major player in global energy markets due to its colossal natural resources. It has the world's tenth-largest natural gas (NG) reserves and is the sixth-largest exporter of natural and liquefied gas. Based on the annual report of the Algerian Ministry of Energy for 2018 [1], the total energy production reached 166.5 million Ton Equivalent of Petroleum (MTEP), of which 100.8 MTEP was exported in its different forms, and only 1.5 MTEP was imported. Regarding energy production, the primary electric load production saw a large increase from 635 GWh to 783 GWh over the year of 2018, scoring an increase of 25%, while the natural gas production had a minor increase of 97 Bm^3 with an estimated increase of 0.9%.

In terms of national consumption, there was an important increase of 7.7% reaching 65 MTEP compared to 2017. This increase was mainly to the rise in natural gas consumption which saw a significant increase of 13.4%, representing 65% of total energy consumption. This was in addition to a 2.9% increase in electric load consumption, with 90% of Algerian electricity is being produced by natural gas-fired power plants [2].

Although the core of the Algerian economy is its energy sector, the growing production and consumption of energy comes at a big environmental cost due to emission of pollutants. Therefore, investing in renewable energy sources is a viable medium and long-term solution. Due to its geographical location, Algeria has one of the biggest solar energy potentials in the world with an estimated 13.9 TWh per year; this is in addition to other renewable energy sources, such as wind and biomass [3]. RE is the major axis of the national energy program devoting an important part to solar thermal and solar photovoltaic sources. By 2030 solar energy is expected to reach around 37% of national electricity generation (12,000 MW for the domestic market along with an export potential of up to 10,000 MW). Despite a fairly low potential, the

URI: https://hdl.handle.net/10125/79641
978-0-9981331-5-7
(CC BY-NC-ND 4.0)

program does not exclude wind power, which constitutes the second development axis and whose share should be around 3% of electricity production in 2030.

In summary, this paper makes the following contributions:

i) A comprehensive study of the RE fields of Adrar (Algeria) both for the wind power (Kabertene) and the photovoltaic (PV).
ii) The development of LSTM models for short-term RE forecasting.
iii) Calculation of CO_2 emissions for equivalent electric load produced using fossil fuels, and the calculation of estimated reduction in CO_2 from using RE.
iv) The work is applied to a real case study of the region of Adrar using real data provided by the national electricity and gas producer and distributor company called SONALGAZ.

2. Related works

Energy forecasting is a wide field, and can be divided into three categories depending on their forecasting horizon: short-term, medium-term, and long-term. Different research has been conducted on energy forecasting where several methods and approaches were used; Soldo [4] presented a survey of forecasting natural gas consumption. The paper described detailed insights on the methods, data and results in the published research papers. The methods that have been applied in those studies can be divided into two main categories: firstly, the traditional time series prediction techniques such as autoregressive moving average (ARMA) [5], non-linear regression techniques like regression trees [6] and support vector regression (SVR) [7], and Kalman filters [8]. The second category consists of artificial intelligence-based methods, particularly: fuzzy logic as in [9], where a hybrid model composed of an Adaptive Neuro-Fuzzy Inference System (ANFIS) and an Auto-Regressive Integrated Moving Average (ARIMA) were employed to forecast annual Iranian energy consumption. Support Vector Machines (SVM) are also frequently used in this area of study [10-11]. However, the most frequently successfully used forecasting technique in several studies is the Artificial Neural Network (ANN) [12], Tonkovic et al. [13] used a Multi-Layered Perceptron (MLP) and Radial Basis Function (RBF) to forecast the next 24h natural gas consumption in Croatia. [14] used several MLP to predict the gas demand in the Polish city of Szczecin in any hour or day of the year taking into consideration weather and calendar inputs. Laib et al. [15] employed multiple MLPs to predict the yearly gas consumption in Algeria, where each MLP was used to predict the consumption in a specific area before summing all the results to get the total consumption. Jetcheva et al. in [16] developed several ANNs to forecast the next 24h electricity load and divided the dataset into subsets, where each subset was used to train a different ANN. Taspinar et al. [17] used RBF, MLP and SARIMAX models to forecast the short-term gas consumption in Sakarya (Turkey). Hsu et al. [18] presented a two-phased ANN model to forecast the short-term load in Taiwan, the first phase was used to forecast the daily load pattern, while the second phase was used to predict both minimum and maximum loads. In order to forecast the solar energy in the next month in hourly steps, Abuella and Chowdhury [19] implemented an ANN using a dataset that consisted of fourteen meteorological variables and compared the obtained results to multiple linear regression (MLR) and persistence models. Bhaskar and Singh [20] described an approach that consists of two phases in order to forecast wind energy; in the first phase, the wind speed for the next 30 hours was forecasted using an adaptive wavelet neural network (AWNN). In the second phase, a MLP was used to map the predicted wind speed into wind power.

In addition to traditional shallow ANN, researchers in recent years have explored new types and topologies of ANN, namely, deep learning networks. These networks showed promising results in time series forecasting and they are gaining increasing popularity [21], Peng et al. [22] used a Multilayer Restricted Boltzmann Machine to forecast four hours in advance of wind power production, this type of ANN is characterized by a strong feature interpretation ability. Kong et al. [23] compared LSTM to other benchmark models such as MLP and k-Nearest Neighbors in a residential short-term load forecasting problem; the results showed that the LSTM outperformed the rest of the models. Laib et al. [24] used a hybrid approach to forecast the short-term natural gas consumption. The approach is composed of a MLP to estimate the next day profile, and LSTM models to forecast the consumption. Wang [25] implemented a framework to forecast solar power generation for 24 hours in advance, the framework consists of a LSTM forecasting model with time correlation principles. Hossain and Mahmoud [26] developed two LSTM forecasting models for short-term electric load forecasting, where one model is used to forecast a single step ahead, while the second predicts multi-step intraday rolling horizons, historical load data was used in addition to weather data. Wang et al. [27] used a LSTM to model both short-term and long-term electric load for both residential and commercial consumers, the LSTM is guided by a pinball loss and based on a dataset from Ireland. Muzaffar and Afshari [28] used LSTM for short-term load forecasting, the used data consisted of 13 months of hourly observations of electric load in addition to weather related exogenous inputs. Kumar et al. [29] presented an approach for forecasting the electric load using LSTM and GRU models. For computation and training, spark and a cluster of machines were used to reduce the training time and lower the error rate. Bouktif et al. [30] focused on both short-term and medium-term electric load forecasting by proposing an approach that consisted of a LSTM model for load forecasting, a genetic algorithm for optimizing the LSTM hyper-parameters, and finally, feature selection for removing unnecessary or redundant features. Other research papers demonstrated that LSTM can be reliable in most forecasting problems, such as stock market predictions [31] and wind speed [32].

The above works are similar to the one presented in this paper. However, they focus mainly on forecasting the energy production and consumption and they ignore its cost. In this work, we solve two problems, the first one is short-term forecasting of RE by proposing efficient LSTM models, and the second is estimating the costs of energy production in terms of CO_2 emissions and examining the benefits of switching to RE sources. Furthermore, this work is practically applied to the region of the north African desert. As such, the results are very valuable for determining the future of the energy sector, as well as the best way to obtain good performances in the region.

3. Renewable energy production in the region of Adrar

The region of Adrar is located in the southwest of Algeria, more than 1400 km from the capital Algiers and falling between the meridians: 6 ° W and 2 ° E, and the parallels 32 ° and 20 ° North. Adrar has 399,712 inhabitants over an area of 424,948 km² which is about 18% of the total area of Algeria, and has a population density of 0.9 inhabitants per km². Adrar was chosen for the implantation of wind and PV farms due to its interesting geographical location that provides ideal solar and wind conditions.

Oudrane et al. [33] conducted a detailed study about the solar potential of the region and found that the south-facing facade in the summer season is the most optimal for obtaining a very high density of the solar flow. Furthermore, the optimal solar gain is recorded in the month of July with a density of 245.48 W/m^2, which is considered as one of the highest ratios in the world. In addition to the solar energy potential, wind energy is also interesting, as the frequency of fast and strong winds is very high over the year, in particular the sirocco wind reaches 100 Km/h. Also, sand winds are very common throughout the spring season.

Based on that potential and since Adrar is not part of the interconnected electrical grid, this region was chosen to hold some of the most important RE projects and plans.

3.1. Adrar's photovoltaic farm

A new photovoltaic 20 MW capacity power plant has been put into service at the level of the RE research unit in Adrar. The project's goal is to test the energy efficiency of such an installation in the Saharan regions and derive a scientific database that could pave the way for possible generalization. Figure 1 illustrates the PV power plant of Adrar.

Figure 1. Adrar's PV power plant

3.2. Kabertene wind farm

Kabertene's wind farm for electricity generation is situated in the commune of Tissabit (80 km north of Adrar). From a partnership between Algeria and France, the first of its kind on the national scale, it is considered to be a successful model for harnessing renewable and clean energy. The wind farm consists of dozens of wind turbines based on field and technical studies that take into account the wind current that characterizes the region. This wind farm ensures renewable and a clean alternative production of 10 MW of electrical power.

Kabertene's experience allowed the energy producers to know about some of the difficulties and obstacles that others may face with such types of power plants, such as extreme temperatures, the impact of desert dust on turbines, intermittency and its impact on the network. Figure 2 shows Kabertene's wind farm.

Figure 2. Kabertene's wind farm

Currently, the RE production from both wind and solar farms, is nearly 40% of the 60 to 100 MW produced in the region when meteorological condition are optimum.

3.3. Available data

The presented work was validated using datasets provided by the national energy distribution company SONALGAZ concerning RE types (PV and wind energy). The datasets consist of historical load values of PV and wind turbines. In addition a set of 3 exogenous inputs were used, which are: temperature, irradiance and wind speed. The data is subsampled every 15 minutes and covers the period from January 2016 to April 2017.

The electric load produced from both PV panels and wind turbines are the main variables. The values are expressed in megawatt-hours (MWh) and vary between 0 to 19.4 MWh and from 0 to 9 MWh for PV and wind turbines, respectively. The total solar irradiance (TSI) is the total intensity of radiative energy coming from the sun received by a surface of 1 m² from the top of the Earth's atmosphere. The irradiance of this series varies in an interval between 0 and 1237.8 Watt / m² approximately. These values are zero at night and reach peak values between 12pm and 2pm. For temperatures, the values are measured in degree Celsius (C°), and vary between 0 and 50 (the peak values are observed between 12 pm and 2 pm in the months of summer). The wind speed is expressed in km/h, the values vary between 0 and 18 km / h, these values are not correlated with time but with sandstorms that can cover the solar panels and decrease their efficiency and therefore the energy production. High wind speeds will affect irradiance and therefore production. Therefore, wind speed must be taken into account as an exogenous variable in modeling PV electrical load production. Figure 3 shows the exogenous inputs.

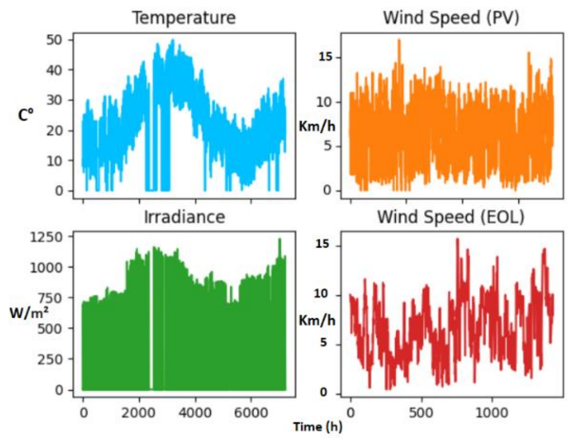

Figure 3. Available exogeneous data samples

4. LSTM neural networks as a modeling tool

Forecasting is a technique that consists of using past data to forecast future values and future trends using various methods. Machine learning techniques and in particular ANN is known to be one of the most popular paradigms in this field. ANNs are a collection of artificial intelligence-based algorithms modeled after biological neural networks and are designed to recognize patterns. ANNs copy the human and animal nervous system and their information processing capabilities. An ANN is composed of layers of interconnected nodes called neurons that are the core of these networks. The information passes from one neuron to another through weighted links.

The fact that an ANN network is composed of multiple single neurons of different types led to several different topologies, such as feed-forward, recurrent neural networks (RNN), and self-organizing maps. RNNs are radically different from the traditional neural networks called feed-forward. Feed-forward neural networks pass the data from the input layer to the output, whereas RNNs have a feedback loop. RNNs are sequence-based models. This makes them a suitable solution for time series forecasting problems as they are able to learn the temporal dependence between past and present information. However, RNNs suffer from some limitations, for instance, they can suffer from exploding and vanishing gradient problems [34, 35] which lead to difficulties in learning long sequences. Therefore, in order to overcome these drawbacks, [36] presented the long short-term memory (LSTM), a variant architecture of RNN that includes a memory cell. This was later enhanced by Gers et al. in [37] by including a forget gate. Therefore, a typical LSTM is composed of a cell, an input gate, a forget gate, and an output gate, and its output can be a sequence of a variable length. Figure 4 shows the structure of an LSTM [38].

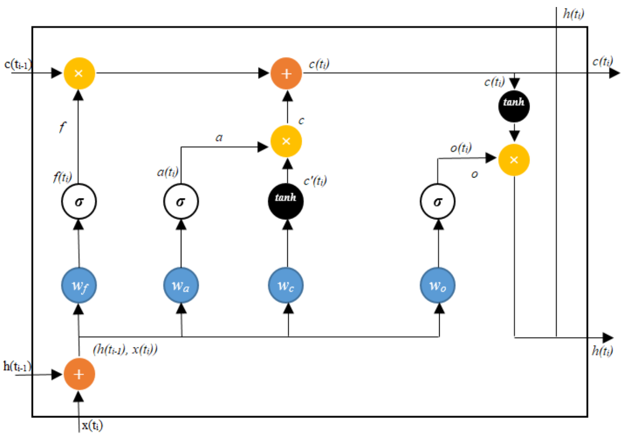

Figure 4. The structure of an LSTM block

- $x(t_i)$ is the input vector
- $h(t_i)$, $h(t_{i-1})$ are the output values at time i and i-1
- $\{w_c, w_a, w_f, w_o\}$: are the weights of the internal state, input, forget, and output gates.
- $\{w_{hc}, w_{ha}, w_{hf}, w_{ho}\}$: are the recurrent weights
- $\{b_c, b_a, b_f, b_o\}$: are the biases
- $\{c(t_i), a(t_i), f(t_i), o(t_i)\}$: are the output values.

Based on the above notations, [38] described the LSTM functioning as follows:

The forget gate $f(t_i)$ uses $x(t_i)$ and $h(t_{i-1})$ as inputs in order to compute the information to be conserved in $c(t_{i-1})$ using a sigmoid activation, the input gate $a(t_i)$ uses the inputs $x(t_i)$ and $h(t_{i-1})$ to calculate $c(t_i)$, and the output gate $o(t_i)$ regulates the output of an LSTM cell by taking into consideration the cell state $c(t_i)$ and using tanh and sigmoid layers. The equations below represent the LSTM's forward learning:

$$a(t_i) = \sigma(w_a x(t_i) + w_{ha} h(t_{i-1}) + b_a \tag{1}$$

$$f(t_i) = \sigma(w_f x(t_i) + w_{hf} h(t_{i-1}) + b_f \tag{2}$$

$$c(t_i) = f_t \times c(t_{i-1}) + a_t \times \tanh(w_c x(t_i) + w_{hc}(h(t_{i-1}) + b_c) \tag{3}$$

$$o(t_i) = \sigma(w_o x(t_i) + w_{ho} h(t_{i-1}) + b_o \tag{4}$$

$$h(t_i) = o(t_i) \times \tanh(c(t_i)) \tag{5}$$

Where σ and *tanh* are activation functions and × is the point-wise multiplication.

Therefore, the outlines of an LSTM learning process are as follows:

- A forward pass, where the output is calculated using the equations (1-5).
- Computing the error of each layer between the output and the input.
- A backward pass by propagating the error backwardly to the input gate, cell, and forget gate.
- Updating the weights based on the error and by using an optimization algorithm.

In order to forecast the electric load for both solar and wind energy, a dedicated LSTM model for each type of energy was developed. Choosing the best architecture for the LSTM models requires tuning several hyperparameters, e.g., choosing the number of hidden layers and the number of neurons in each layer, setting the learning and dropout rates, choosing a suitable lag size (number of used past values), batch size, and the number of epochs. Hence, several tests and trials were performed with different combinations of hyperparameters in order to select the best topology based on the validation errors. Table 1 presents some of the tested hyperparameters values.

Table 1. Tested hyperparameters values

Hyperparameter	Values
Number of hidden layers	[1, 2, 3]
Number of neurons in each layer	[10, 20, 40, 80, 160, 320, 500]
Lag size	[1, 2, 3, 5, 7, 12]
Learning rate	[0.0001, 0.001, 0.01]
Dropout rate	[0.1, 0.2, 0.3]
Batch size	[8, 16, 32, 64]
Number of epochs	[500, 1000, 1500, 2000]

For the optimisation algorithm we used the Adam optimizer [39] for both models. More details about the models are as follows:

The PV model: To forecast PV electric load production, we used a dataset for Adrar, which consists of 7237 data points (hourly steps), 70% of the data were used for training, while 30% were used for testing the model, which are unknown data that was not used in the training. The topology of the used LSTM is composed of two hidden layers, with 50 neurons in the first hidden layer and 30 in the second. The input vector consists of three lagged values of each one of the four input variables, which are the past load values, temperature, wind speed, and irradiance.

The Wind energy model: Similar to the PV model, the LSTM consists of two hidden layers with 50 and 30 hidden neurons. The input vector consists of

2 lagged values of the two used variables: past load and wind speed.

5. Results and discussion

In this section, the results are presented, discussed, and compared with some of the field's benchmark models.

5.1. Forecasting the energy

In order to decide the most suitable topologies and hyperparameters for our models, we performed several tests and used the root-mean-squared-error (RMSE) and the mean-absolute-error (MAE) evaluation metrics, which are computed using equations (6) and (7) where a_i is the predicted value, p_i is the observed value, and i is the length of the input vector.

$$RMSE = \sqrt{\frac{1}{N}\sum_{\mathrm{i}}^{N}(\mathrm{a}_i - \mathrm{p_i})^2} \quad (6)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|a_i - p_i| \quad (7)$$

Table 2 summarizes the used hyperparameters of both models that were selected based on the validation errors obtained from the multiple performed tests. Table 3 presents the obtained performances in terms of RMSE and MAE metrics, the solar energy model achieved a MAE of 0.024 and a RMSE of 0.026, while the wind energy model achieved a MAE of 0.109 and a RMSE of 0.166 on the test dataset.

Table 2. The used hyperparameters

Models	Hidden layers size	Lag size	Learning rate	Dropout size	Batch size
Solar energy	[50-30]	3	0.001	[0.1-0.1]	16
Wind energy	[50-30]	2	0.001	[0.1-0.1]	16

Table 3. Models' performance

Models	MAE		RMSE	
	Train	Test	Train	Test
Solar energy	0.021	0.024	0.019	0.026
Wind energy	0.106	0.109	0.105	0.166

Figures 5 and 6, compare the real and the forecasted values of a 24-hour sample for a winter's day for both wind and solar models. The models were able to forecast the daily production trends very accurately over the entire 24-hour period.

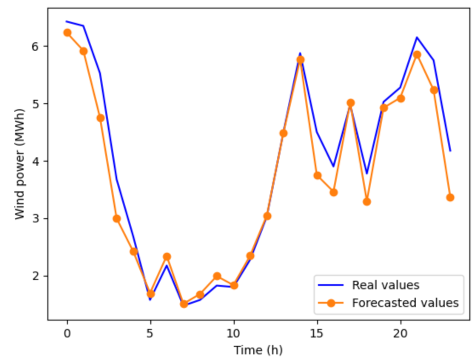

Figure 5. Forecasting wind load production

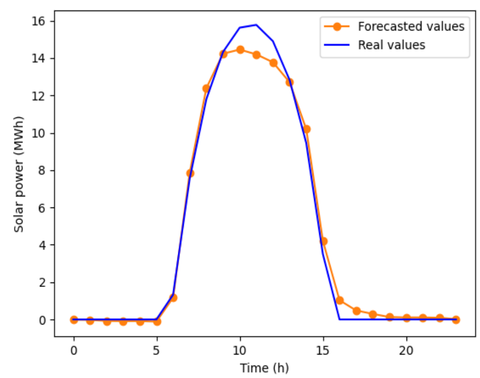

Figure 6. Forecasting Adrar PV load production

5.2. Comparison with benchmark models

We compared our LSTM models against some of the most used forecasting techniques in the literature, mainly: ARIMA, SVR, and feed forward Mutli-layered perceptron (MLP) networks, in order to validate the obtained performance of our models.

5.2.1. SVR

Support vector regression (SVR) is an extension of the traditional support vector machine (SVM) and it has been used successfully to address regression problems on different research areas [40]. SVR keeps all the main characteristics and principals of SVM for classification with some minor changes. The most important hyperparameter in SVR is the kernel function, in our case we used radial basis function (RBF).

5.2.2. ARIMA

ARIMA which stands for Autoregressive integrated moving average, is a first-class time series forecasting technique introduced by Box and Jenkins [41]. ARIMA models are defined by three parameters:

p, q, and d, which refer to the number of lag observations included in the model, the moving average parameters, and the number of differencing passes respectively. In our experiments we set the parameters p to be equal to the used lag size in the LSTM models, and we set the parameter q to 0 and d to 1.

5.2.3. MLP

The last used benchmark model is a feed forward neural network, which is one of the most widely used models for forecasting and function approximation problems [42]. In our experiments we used two hidden ANNs with a sigmoid activation function.

5.2.4. Comparison and discussion

All the tested models received the same training and test data, the evaluation metrics MAE and RMSE were used to compare the performances of the models. The obtained performance of each model is presented in table 4.

Table 4. Comparison between LSTM and other Benchmark models

Metric	Model	LSTM	MLP	SVR	ARIMA
RMSE	Solar energy	0.026	0.241	0.380	0.217
	Wind energy	0.166	0.344	0.338	0.214
MAE	Solar energy	0.024	0.222	0.073	0.137
	Wind energy	0.109	0.311	0.078	0.146

Based on the obtained results, all the tested methods achieved good and acceptable performances with a small advantage for our LSTM models as they achieved smaller MAE and RMSE errors. Therefore, despite the good performances of the benchmark models especially ARIMA and MLP, the proposed LSTM models relatively enhanced the forecasting quality on the available datasets.

5.3. Forecasting the costs of Adrar's energy demand

In this work we address the issue of mixed energy sources for electrical production (RE and fossil energy) in Adrar's region; hence, adding both PV and wind energy forecasting and subtracting it from the daily demand of Adrar. This gives us the load to be produced using fossil energy via gas turbines as illustrated in figure 7. Forecasting the remaining load to be produced may be helpful to optimize the quantity of NG needed for production. Although NG is highly subsidized by the government and therefore relatively inexpensive, optimization of its use benefits the environment by reducing the use of fossil fuels, decreasing CO_2, and increasing air quality

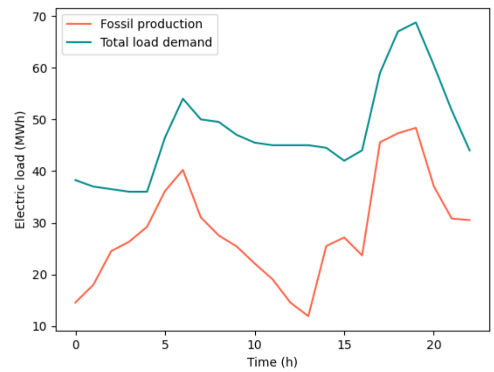

Figure 7. Adrar's fossil production and global energy demand (The difference is filled by RE)

As illustrated in Figure 7, the evening is mostly covered by fossil production using Adrar's gas-fired power plant. RE production covers an important portion of the demand from 6am to 4pm, which is mainly due to the fact that the main renewable source is solar, which tends to decrease to zero after sunset (around 7pm). This limitation cannot be overcome unless the wind farm of Kabertene is extended, and even then, it will still rely on wind speed. The best solution would be to store excess PV production and release it at peak time, but this is a totally different issue in terms of technological constraints.

Thus, to calculate the equivalent amount of NG that was used to generate the fossil energy output, the equation (8) from the U.S Energy Information Administration [43] was used:

$$AG = HR / HV \tag{8}$$

Where *AG* is the amount of gas used to produce one *kWh*, *HR* is the heat rate of the power plant and *HV* is the heat value of the used fuel. Hence, assuming that the *HV* of natural gas is *1,023,000 Btu/Mcf* and the average *HR* of a natural gas-fired power plant is *8,039 Btu/kWh*, producing *1 kWh* of electric power requires burning *0.00786 Mcf* of natural gas, which is equivalent to $0.22\ m^3$.

Secondly, to compute the CO_2 emitted from producing electric power using fossil energy, we used the emission factors from [44], which indicates that the CO_2 equivalent of burning natural gas is 0.0551 tCO_2/Mcf which is equal to 0.0019 tCO_2/m^3.

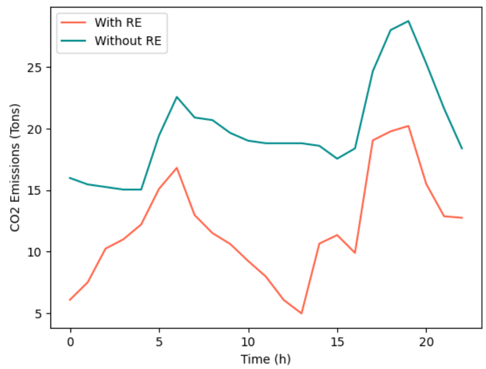

Figure 8. Comparison of CO_2 emission in the case of using and not using RE

Figure 8 above compares the emitted amount of CO_2 if all of the produced electric demand in Adrar was produced using only the NG fired power plant with the emissions using RE to produce a portion of the load. It can be seen that RE can help reduce the emissions by up to 15 tons of CO_2 per hour (25%). Figure 9 illustrates a comparison between the consumed amount of NG in the two cases (whether renewable energy sources were used to generate the electric load or not).

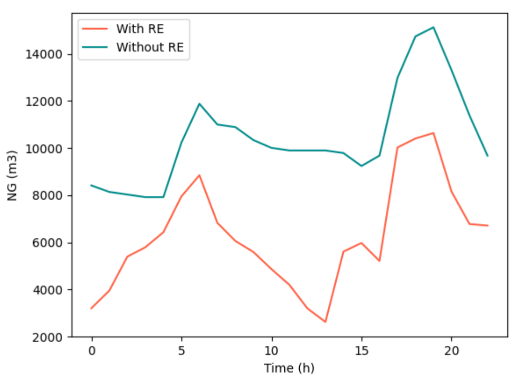

Figure 9. Comparison of NG consumption in the case of using and not using RE

6. Conclusion

The world is facing a climate crisis and steps must be taken to reduce the amount of CO_2 in the atmosphere. Short term load forecasting is an essential task in order to define, at an hourly or even quarterly basis, the electric load to be produced. This should be matched with the daily future demand for an optimal distribution of production resources and to avoid any energy shortage or waste.

This paper presented the modeling steps of both wind turbine and PV electrical energy production fields in the region of Adrar, Algeria in terms of electrical load. The artificial intelligence approach used is LSTM neural networks. LSTM has proved to be a suitable solution for short-term forecasting by achieving good performances and accuracy. The production forecast accurately evaluates the remaining load to be produced using traditional fossil capabilities. Thus, generating substantial savings in terms of NG and environmental protection in terms of reducing CO_2 emissions.

Looking forward to reducing CO_2 emissions, we hope that in some way the approaches developed in this paper will help us to be more resilient towards the effects of climate change.

For future work we aim to generalize the approach to include more regions of Algeria, as well as including more energy and air pollution sources.

7. References

[1] Algerian ministry of energy, bilan energetique national 2018, http://www.energy.gov.dz/.

[2] Khadir M.T., Bouziane S.E.: ”Artificial Neural Networks modeling of electrical renewable energy both photovoltaic and wind for the region of Adrar Algeria”. 4th International Conference on Artificial Intelligence in Renewable Energetic Systems. Tipaza, Algeria, 2020.

[3] Bouziane S.E., Khadir M.T., Dugdale J.: “A collaborative predictive multi-agent system for forecasting carbon emissions related to energy consumption”, Multiagent and grid systems, IOSPress, 2021, vol. 17, 39-58.

[4] Soldo B.: “Forecasting natural gas consumption”, Applied Energy, 2012, vol. 92, 26-37.

[5] Huang S., Kuang R.: “Short-term load forecasting via ARMA model identification including non-Gaussian process considerations”, IEEE Transactions on Power Systems, 2003, vol. 18, 673-679.

[6] Lusis P., Khalilpour K., Andrew L., Liebman A.: “Short-term residential load forecasting: impact of calendar effects and forecast granularity”, Applied Energy, 2017, vol. 205, 654-659.

[7] Bai Y., Li C.: “Daily natural gas consumption forecasting based on a structure calibrated support vector regression approach”, Energy Build, 2016, vol. 127, 571-579.

[8] Fagiani M., Squartini S., Gabrielli L., Spinsante S., Piazza F.: “Domestic water and natural gas demand forecasting by using heterogeneous data: a preliminary study”, Advances in neural networks: computational and theoretical issues, 2015, vol. 37, 185-194.

[9] Barak S., Sadegh S.: “Forecasting energy consumption using ensemble ARIMA–ANFIS hybrid algorithm”. International Journal of Electrical Power & Energy Systems, 2016, vol. 82, 92-104.

[10] Jiang P., Li R., Liu N., Gao Y.: “A novel composite electricity demand forecasting framework by data processing and optimized support vector machine”, Applied Energy, 2020, vol. 260.

[11] Lu H., Azimi M., Iseley T.: “Short-term load forecasting of urban gas using a hybrid model based on improved fruit fly optimization algorithm and support vector machine”, Energy reports, 2009, vol. 5, 666-677.

[12] Hippert H., Pedreira C., Souza R.: “Neural networks for short-term load forecasting: a review and evaluation”, IEEE Trans Power Syst, 2001, vol. 16, 44-55.

[13] Tonkovic Z., Zekic-Susac M., Somolanji M.: “Predicting natural gas consumption by neural networks”, Tehniki vjesnik, 2009, vol. 16, 51-61.

[14] Szoplik J.: “Forecasting of natural gas consumption with artificial neural networks”, Energy, vol. 85, 2015, 208-220.

[15] Laib O., Khadir M.T., Chouired L.: “Forecasting yearly natural gas consumption using Artificial Neural Network for the Algerian Market”, 2016 4th International Conference on Control Engineering & Information Technology (CEIT), Hammamet, Tunisia. 2016, 1-5.

[16] Jetcheva J.G., Majidpour M., Chen W.P., Neural network model ensembles for building-level electricity load forecasts, Energy and Buildings, 2014, vol. 84, 214-223.

[17] Taşpınar F., Çelebi N., Tutkun N.: “Forecasting of daily natural gas consumption on regional basis in Turkey using various computational methods”, Energy and buildings, 2013, vol. 56, 23-31.

[18] Hsu Y., Tung T., Yeh H., Lu C.: “Two-Stage Artificial Neural Network Model for Short-Term Load Forecasting”, IFAC-PapersOnLine. 2018, vol. 51, 678-683.

[19] Abuella M., Chowdhury B.: “Solar Power Forecasting Using Artificial Neural Networks”, North American Power Symposium (NAPS), Charlotte, USA, 2015.

[20] Bhaskar K., Singh S.N.: “AWNN-Assisted Wind Power Forecasting Using Feed-Forward Neural Network”, IEEE Transactions on Sustainable Energy, 2012, vol. 3, 306-315.

[21] Langkvist M., Karlsson L., Loutfi A.: “A review of unsupervised feature learning and deep learning for time-series”, Pattern Recognition Letters, 2014, vol. 42, 11-24.

[22] Peng X., Xiong L., Wen J., Xu Y., Fan W., Feng S., Wang B.: “A very short-term wind power prediction approach based on Multilayer Restricted Boltzmann Machine”, IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), Xian, China. 2016.

[23] Kong W., Dong Z., Jia Y., Hill D., Xu Y., Zhang Y.: “Short-term residential load forecasting based on LSTM recurrent neural network”, IEEE Transactions on Smart Grid, 2017, vol. 10, 841-851.

[24] Laib O., Khadir M.T., Mihaylova L.: “Toward efficient energy systems based on natural gas consumption prediction with LSTM Recurrent Neural Networks”, Energy, 2019, vol. 177, 530-542.

[25] Wang F., Xuan Z., Zhen Z., Li K, Wang T., Shi M.: “A Day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework”, Energy Conversion and Management, 2020, vol. 212.

[26] Hossain M., Mahmood H.: “Short-Term Load Forecasting Using an LSTM Neural Network”, Power and Energy Conference, 2020. Illinois, USA.

[27] Wang Y., Sun M., Zhang N., Lu Z., Kang C.: “Probabilistic individual load forecasting using pinball loss guided LSTM”, Applied Energy, 2019, vol 235,10-20.

[28] Muzaffar S., Afshari A.: “Short-Term Load Forecasts Using LSTM Networks”, Energy Procedia, 2019, vol 158, 2922-2927.

[29] Kumar S., Hussain L., Banarjee S., Reza M.: “Energy Load Forecasting using Deep Learning Approach-LSTM and GRU in Spark Cluster”, 5th International Conference on Emerging Applications of Information Technology (EAIT), 2018, India.

[30] Bouktif S., Fiaz A., Serhani M.: “Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: comparison with Machine Learning Approaches”, Energies, 2018, vol 11.

[31] Karmiani D., Kazi R., Nambisan A., Shah A., Kamble V.: “Comparison of Predictive Algorithms: Backpropagation, SVM, LSTM and Kalman Filter for Stock Market”, Amity International Conference on Artificial Intelligence, 2019. Dubai, UAE.

[32] Memarzadeh G., Keynia F.: “A new short-term wind speed forecasting method based on fine-tuned LSTM neural network and optimal input sets”, Energy Conversion and Management, 2020, vol. 13.

[33] Oudrane A., Benaoumeur A., Hamouda : “Étude et Analyse du Gisement Solaire Pour une Région Désertique : Type Adrar“, Communication Science & technology, 2019, 3909-3919.

[34] Bengio Y., Simard P., Frasconi P.: “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994, vol. 5, 157-166.

[35] Kolen J.F., Kremer S.: “Gradient flow in recurrent nets: the difficulty of learning long-term dependencies”, A Field Guide to Dynamical Recurrent Networks, 2001.

[36] Hochreiter S., Schmidhuber J.: Long short-term memory. Neural computation, 1997, vol. 9, 1735-1780.

[37] Gers F.A., Schmidhuber A., Cummins F.A.: “Learning to Forget: Continual Prediction with LSTM”, Neural Computing, 2000, vol. 12, 2451-2471.

[38] Abbasimehr H., Shabani M., Yousefi M.: “An optimized model using LSTM network for demand forecasting”. Computers & industrial engineering, 2020, vol. 143.

[39] Kingma D.P., Ba J.: Adam: “A Method for Stochastic Optimization”. International Conference on Learning Representations (ICLR), 2015, San Diego, USA.

[40] Ahmad M., Adnan S. M., Zaidi S., Bhargava P.: “A novel support vector regression (SVR) model for the prediction of splice strength of the unconfined beam specimens”, Construction and building materials, 2020, Vol 248.

[41] Box G.E.P., and Jenkins G.M.: Time series analysis: Forecasting and control. Holden-Day, San Francisco. 1996.

[42] Kizilaslan R., Karlik B.: Comparison Neural Networks Models for Short Term Forecasting of Natural Gas Consumption in Istanbul. First International Conference on the Applications of Digital Information and Web Technologies (ICADIWT), Ostrava, 2008, pp. 448-453.

[43] https://www.eia.gov/tools/faqs/ Last accessed: 14/06/2021.

[44] https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references. last accessed: 14/06/2021.