Impact of Input Data Structure on Convolutional Neural Network Energy Prediction Model

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***Abstract*—Energy demand continues to increase with no prospect of slowing down in the future. This increase is caused by several sociological and economical factors such as population growth, urbanization and technological developments. In view of this growth, it becomes crucial to predict energy consumption for a more accurate management and optimization. Nevertheless, consumption estimation is a complex task due to consumer behaviour fluctuation and weather alterations. Several efforts were proposed in the literature. Almost, all of them focused on improving the prediction model to increase the accuracy of the results. They use the LSTM (*Long-Short Term Memory*) model to reflect the temporal dependencies between historical data despite its spatial and temporal complexities. The main contribution in this paper is a novel and simple Convolutional Neural Network energy prediction model based on input data structure enhancement. The main idea is to adjust the structure of the input data instead of using a more complicated deep learning model for better performance. The proposed model was implemented, tested using real data and compared to existing ones. The obtained results showed that the proposed data structure has a great influence on the model performance measurement.**

Keywords*—Deep learning; convolutional neural network; energy consumption; energy prediction

I. INTRODUCTION

The demand for energy increases with population size and economic growth and also depends on the consumers' behavior and their deployed appliances. Faced with this growth, consumption prediction is a crucial task that enables efficient and optimized energy management. Several techniques have been developed to predict demand for the next hours, days, weeks, months and even years. Most of them are based on historical data [1] and use Machine Learning or Deep learning models such as Artificial Neural Networks (ANN) [2], Support Vector Machine (SVM) [3], Convolutional Neural Network with Long- Short Term Memory (CNN-LSTM) [4], etc.

Deep Learning (DL) is an advanced Machine Learning approach that has been widely applied in many fields and has shown great performance for many problems such as image processing [5], [6], computer vision [7], [8], natural language processing [9], [10] and time series prediction [11], [12]. Also, the DL approaches have provided good accuracy for energy systems such as solar irradiance forecasting [13], [14] and wind speed prediction [15], [16]. Recently, DL approaches have been widely applied to predict the quantity of energy to be consumed. In most of the time, the consumed energy data are presented in time series. Energy consumption forecasting is therefore a multivariate time series forecasting problem. LSTM is a Recurrent Neural Network (RNN) specification that is characterized by the capacity to control the flow of separate information [17] and mainly to detect temporal dependencies between data [18]. These advantages make LSTM effective for short-term or near-real-time forecasting. Consequently LSTM has been widely used for energy consumption prediction.

All these efforts focused on enhancing the ML/DL existing models for a better accuracy regardless of the complexity of the resulting one. However none of them dealt with adjusting the input data to attain same and even better performance. The main contribution of this paper is to propose a new DL based model that shows the impact of the input data structure on the prediction results.

The remaining of the paper is structured as follows: the next section describes the various existing researches that deal with energy consumption prediction using CNN and LSTM. Section III defines the CNN model and explains the proposed one. Section IV discusses the experimental evaluation and the conclusion is presented in Section V.

II. RELATED WORKS

During the last two decades, several researchers have contributed to the solving of energy consumption prediction problems, resulting in a wide range of studies. These studies can be divided into two categories: those that use static methods, while others apply physical methods. Among static methods, Machine Learning techniques have been widely applied for predicting energy consumption. In [19], authors applied to the Support Vector Machine (SVM) while in [20], authors proposed Artificial Neural Networks (ANN) based solutions. ANN based models were also applied to different datasets in order to analyze them and select the relevant ones. However, recent trends are oriented towards applying Deep Learning models as Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), LSTM, etc.

In [21], the authors presented two approaches based on LSTM for energy load prevention, and tested them on both data steps of one hour and one minute. The first approach uses the standard LSTM while the second one uses the Sequence to Sequence architecture. In [22], the authors applied CNN to predict the energy load per hour within a smart grid. Their aim is to demonstrate the effectiveness of their proposed CNN compared to other convolutional models. Another CNN model for energy load prediction was discussed in [23]. The authors proposed the use of a set of historical input loads on which they applied convolutions. The obtained results were passed to a fully connected layer that produced the final output. Experimental tests showed that the results of their proposed model are similar to ANN, but outperforms those of Support Vector Regression model. As for [24], the objective was to solve the problem of load profile uncertainty for predicting household energy consumption. To do this, the authors proposed a model based on RNN where they grouped the load profiles in an input pool. The results showed that this model performs better than the classical RNN, Support Vector Regression and Auto Regressive Integrated Moving Average in terms of RMSE. The authors of [25] provided a Recurrent Inception Convolution Neural Network RICNN to solve the problems of existing RNN methods for daily energy load prediction. The proposed model combines RNN and one-dimensional CNN (1-D CNN). The obtained results proved the efficiency of the proposed model compared to benchmarked multi-layer perceptron, RNN and 1-D CNN.

In the context of a short-term prediction for residential energy consumption, an LSTM model has been proposed in [26]. This model is called Quantile LSTM (Q-LSTM) whose objective is to predict the probabilistic residential load with LSTM in quantile term. The results showed the efficiency of the proposed method compared to traditional ones in terms of averaging quantile score. As for the prediction of future energy demand, the authors in [27] defined and tested two types of approaches, the first one based on CNN and the second one based on neural networks and two optimization algorithms, the Genetic Algorithm (NNGA) and the Particle Swarm Optimization algorithm (NNPSO). The authors in [28] proposed a model based on feed forward back propagation neural network named FFBPNN. The proposed model involves four layers which are data collection layer, preprocessing layer, prediction layer and evaluation layer. The last layer provides the performance measures MAE, MAPE and RMSE. In 2021, in [29], authors presented a multi-seasonal short-term memory network LSTM-MSNet for time series forecasting with multiple seasonal models. The evaluation of the LSTM-MSNet model shows that this model has the best execution time and accuracy compared to existing ones. A new hybrid model for energy consumption prediction named DB-NET was presented in [30]. The proposed model combines the dilated CNN (DCNN) and bidirectional LSTM (BiLSTM). Experimental tests proved the efficiency of the DB-Net model.

In [4], the authors proposed a CNN-LSTM model combining both CNN and LSTM. This model extracts (1) spatial features using the CNN layer which allows feature extraction between multiple variables and (2) temporal features using LSTM which models irregular temporal information. Although this latter yielded to a good prediction performance, an improved EECP-CBL version has been presented in [31]. The experimental results of EECP-CBL proved that it is more efficient in predicting energy consumption than the CNN-LSTM model and other existing ones. The authors of [32] presented a new hybrid M-BDLSTM method combining CNN with the multi-layer bidirectional long-term memory method. Recently, in 2021, the authors of [33] proposed a meta-heuristic based on LSTM and Butterfly Optimization Algorithm (BOA) for the prediction of energy consumption. Butterfly Optimization Algorithm was used to discover the dynamic time series. This model showed a lower error rate on the IHEPC dataset [34] compared to existing one. In 2022, [35] they proposed a hybrid model combining CNN and echo state network allowing both power generation and consumption forecasting. In this model, CNN performed the extraction of features from historical data while the echo state network ensured the learning of temporal features. The experimental results of this model on the IHEPC dataset showed a good performance in terms of RMSE, MSE, NRMSE, and MAE.

All these efforts contributed to improve the efficiency of energy prediction models. Their main goal focus on updating and enhancing previous ML/DL models for a better performance. They proceeded by combining several Machine Learning and Deep Learning techniques or/and adding optimization algorithms to increase the results accuracy. Nevertheless and despite the effectiveness of these models, we believe that it is possible to improve the prediction performance by using a less complex Convolutional model and different input data structures. The idea is to focus on finding the optimal data structure for the input data that may improve the results of prediction without resorting to sophisticated, complex and time/space consuming ML/DL models.

III. Proposed CNN Model

An accurate prediction model for energy consumption is essential to simulate an energy management system between consumers and suppliers in order to optimize the energy use and to minimize its waste. However, the estimation process is a complex task due to the influence of several environmental factors and to the users' behavior.

Traditional network-based techniques are the main models to predict future energy consumption [36]. These models are based on the short-term memory for considering dependencies between the input data. Other models involve the LSTM network for integrating historical context. Nonetheless, these solutions would increase the time and space complexities of the estimation process.

In this article, we focused on simplifying the temporal and spatial complexity of existing models. Therefore, the principal contribution of our research is to reflect temporal dependencies between historical data without using the LSTM model. For this purpose, we tried to turn our investigation towards the input data rather than the deployed models. Hence, we thought of *i*) adjusting the input structure representation to emerge the time-series relationship between the historical data, *ii*) applying a simple CNN-based model to predict the future energy consumption with higher accuracy. We choose the CNN model presented in [37] and [38] for its promising results in both electricity consumption prediction [37] and load forecasting [38].

A. Input Data Proposed Structures

Since the meteorological seasons divide the year into four periods (Spring, Summer, Autumn and Winter) more or less equal, their duration varies from 89 to 93 days. Hence the energy consumption varies according to the weather characteristics of each season; For example in summer the temperature is high and therefore the need to use air conditioners increases. In addition, the climate of one season has a great impact on

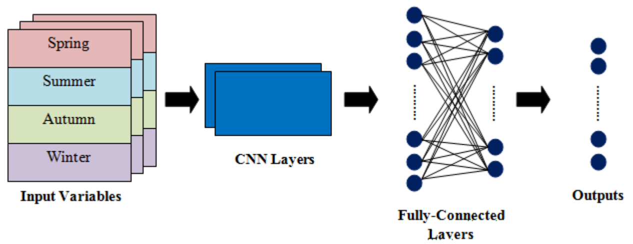

Fig. 1. Overview Architecture of Proposed Model using the Serial Matrix.

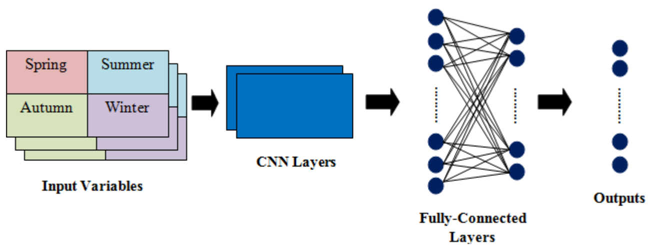

Fig. 2. Overview Architecture of Proposed Model using the Cycle Matrix.

the climate of the following ones. Generally, a too cold winter is usually followed by a too hot summer.

All existing researches manipulates the historical information of the energy consumption in a sequential form. No physical link between same season of different years, despite their intrinsic logical one. Most efforts rely on the LSTM model to take into consideration the logical relationships among consumption data. Our idea is to find a simpler way to reflect the logical link between the same season through several years. Therefore, we thought about improving the structure input data instead of investigating on the underlying prediction model. So the main idea of this paper is to present the data in a 3-dimensional matrix to be able to **(1)** maintain the different states of the same season over several years and **(2)** model the temporal dependencies between the different seasons.

In this paper, we will employ two different data structures for the input data. For the first data structure, we will use a matrix that indicates the four seasons of a year in a series manner. In this case the height of this matrix is the number of days in a year, its width is the number of features and its depth represents the number of years in the dataset. Fig. 1 shows the overall architecture of the proposed model using the first matrix form.

For the second proposed data structure, the data are organized in a cycle, i.e. in the same row we include the data of two consecutive seasons (Spring and Summer followed by Autumn and Winter). In this matrix the number of rows is half the number of days in a year, the width is twice the number of variables and the depth is the number of years in the dataset. The architecture of the model using this matrix is given by the Fig. 2.

The input of our model is the 3-D matrix on which two CNN layers are applied to extract the input variables which are transmitted to the two fully connected layers to generate the prediction of future energy consumption.

B. CNN-based Model

In our model we used convolutional 3D Layers, Pooling 3D Layers and fully connected Layers. In detail, we used two convolutional layers with a filter number equal to 64 and a kernel size (3,3,2). These two layers are followed by two max-pooling layers with a kernel size of (3,2,1). The max-pooling layer allows reducing the network computational cost as it selects only the most important features. Then flatten layer is applied to flatten the feature vector. Finally, two fully connected layers are used to adjust the result by providing the estimated energy consumption. The architecture and configuration of the proposed model are detailed in Table I.

TABLE I. ARCHITECTURE OF THE PROPOSED MODEL

Layer Type	Kernel size	Filter size	Parameters
Convolution3D	(3,3,2)	64	832
MaxPooling3D	-	-	0
Convolution3D	(3,2,1)	64	24640
MaxPooling3D	-	-	256
Flatten	-	-	0
Fully connected(128)	-	-	221312
Dropout	-	-	0
Fully connected(364)	-	-	45440

IV. EXPERIMENTAL EVALUATION

In this section, first, we will describe the used dataset. Then, we will exhibit the obtained experimental results expressed in terms of performance measures, including MSE (Mean square error), RMSE (Root MSE), MAE (Mean Absolute error), MAPE (Mean Absolute Percentage Error) and the CPU time (training and testing times). Finally, we will compare the obtained results with existing energy prediction models in the literature.

A. Dataset Description

To evaluate the proposed model and compare its performance with the models described in [4] and [31], we have applied our model to the same dataset used by aforementioned ones. The IHEPC dataset [34] available at UCI (University of California, Irvine) Machine Learning Repository. The data of this dataset are collected from a house located in Sceaux in France over five years from December 2006 to November 2010. This set contains 2,075,259 measurements with 25979 missing values equivalent to 1.25% of the total amount of data. The missing data have been processed in the pre-processing phase.

IHEPC contains nine variables e.i., day, month, year, hour, minute, global active power, global reactive power, voltage and global intensity. In addition to three variables collected from the energy consumption sensors which are sub metering 1, sub metering 2 and sub metering 3. Table II presents all these variables and their meanings as defined in the literature [39].

TABLE II. THE FEATURES OF THE IHEPC DATASET

Variable	Description
Day	A value from 1 to 31
Month	A value from 1 to 12
Year	A value from 2006 to 2010
Hour	A value from 0 to 23
Minute	A value from 1 to 60
Global active power	The household global minute-averaged active power (in kilowatt)
Global reactive power	The household global minute-averaged reactive power(in kilowatt)
Voltage	The minute-averaged voltage (in Volt)
Global intensity	The household global minute-averaged current intensity (in Ampere)
Sub metering 1	This variable corresponds to the kitchen, containing mainly a dishwasher, an oven and a microwave, hot plates being not electric, but gas powered (in watt-hour of active energy)
Sub metering 2	This variable corresponds to the laundry room, containing a washing machine, a tumble-drier, a refrigerator and a light (in watt-hour of active energy)
Sub metering 3	This variable corresponds to an electric water heater, and an air conditioner (in watt-hour of active energy)

B. Evaluation Metrics

Energy consumption prediction is a time-series data problem. Several metrics are used to evaluate the performance of a prediction model. These metrics are based on analyzing the correlation and error between the actual values and the estimated ones. These performance metrics are detailed in [40]. For the proposed model, we used the same metrics as given in [4] and [31] to be able to perform a fair comparison on the same scale, i.e. MSE, RMSE, MAE and MAPE.

1) *Mean Square Error:* MSE is used to measure the average difference between the actual and estimated values as shown in the equation 1.

$$MSE = \frac{1}{N}\sum_{1}^{N}(a-p)^2 \tag{1}$$

2) *Root Mean Square Error:* RMSE is the most widely used one for evaluating current forecasts. It allows finding the difference between the current values and the predicted ones(equation 2).

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N}(a-p)^2} \tag{2}$$

3) *Mean Absolute Error:* MAE measures the mean distance between the actual and predicted values as given in the equation 3.

$$MAE = \frac{1}{N}\sum_{1}^{N}|(a-p)| \tag{3}$$

4) *Mean Absolute Percentage Error:* MAPE expresses the percentage accuracy of the prediction as stated in the equation 4.

$$MAPE = \frac{1}{N}\sum_{1}^{N}|(a-p)| * 100\% \tag{4}$$

with, a and p represent the actual and predicted values, while N is the total number of records.

C. Performance Comparison

From the IHEPC set, we created a daily dataset for the period between March 2007 and February 2010. From this set we have created the two different proposed structures of matrix. For the first one, the matrix in series, we associate the model called *New Model-1* and for the second matrix structure, the model named *New Model-2*. To evaluate these two models, we performed three different experiments. For the first experiment, we considered the first and second years for the training set and the second and third years for the testing set. For the second experiment and in order to avoid duplicating the use of the second year for both training and testing sets, we used the first two years for the training set and we kept only the third year for the testing set. For the last experiment, the first year only is used for the training set and the other two years for the testing set. The two models were implemented with the tensorflow and keras libraries of Python and trained in 100 epochs with Adam optimization. The obtained experimental results were compared with the results given by LSTM, CNN-LSTM [4] and EECP-CBL [31] in terms of the four previously described performance metrics, i.e. equations 1, 2, 3 and 4.

TABLE III. MODEL-1: PERFORMANCE OF THE EXPERIMENTAL METHODS

Model	MSE	RMSE	MAE	MAPE	Training time (s)	Prediction time(s)
LSTM	0.241	0.491	0.413	38.72	106.06	2.97
CNN-LSTM	0.104	0.322	0.191	31.38	42.35	1.91
EEPC-CBL	0.065	0.225	0.191	19.15	61.36	0.71
Exp. 1	**0.017**	**0.131**	**0.022**	**2.29**	**6.01**	**0.18**
Exp. 2	**0.023**	**0.154**	**0.008**	**0.841**	**6.18**	**0.179**
Exp. 3	**0.017**	**0.131**	**0.018**	**1.844**	**5.87**	**0.19**

1) Model-1 Evaluation Results:

a) Experiment 1: In this experiment we selected the first and second years for the training set and the second and third years for the testing set. The performance measures of the proposed model and of the LSTM, CNN-LSTM and EECP-CBL models are presented in Table III. Thus, Fig. 3 and 4 present a comparison of the MSE, RMSE, MAE and MAPE values of our model with existing models. We conclude that the proposed model achieves best results compared to the other models. The MSE value of our approach (0.017) is improved by more than 50% compared to the EECP-CBL model (0.65). Meanwhile, the LSTM and CNN-LSTM models achieve very high MSE values of 0.104 and 0.241 respectively. For the RMSE and MAE measures, the proposed model obtains respectively 0.131 and 0.022 which are the best results compared to the other models. The MAPE value of the proposed model is equal to 2.297 and that of LSTM, CNN-LSTM and EECP-CBL is respectively 38.72, 31.83 and 19.15, we note that this value is improved by about 80% compared to the last model.

Table III and Fig. 5 compare the training and prediction time of the proposed model with the LSTM, CNN-LSTM and EECP-CBL models. The training time of the proposed model is equal to 6.014 seconds while the LSTM, CNN-LSTM and EECP-CBL models require 106.06, 42.35 and 61.36 seconds respectively to train. We can see that the gap in training time is very large between our model and the other models.

In Machine Learning, the most important thing is not the

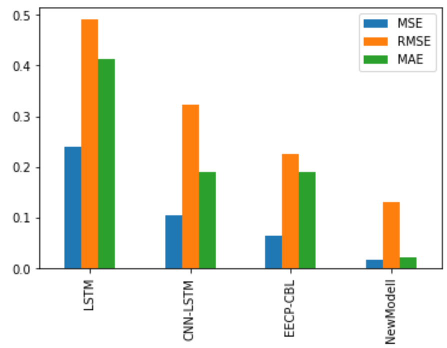

Fig. 3. New Model-1-Experiment-1 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MSE, RMSE and MAE.

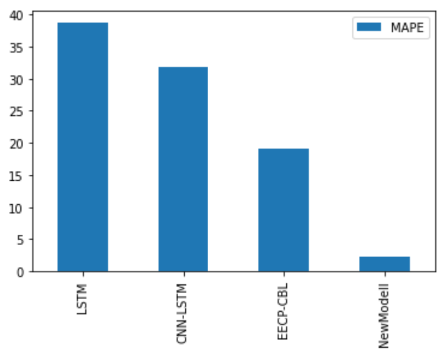

Fig. 4. New Model-1-Experiment-1 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MAPE.

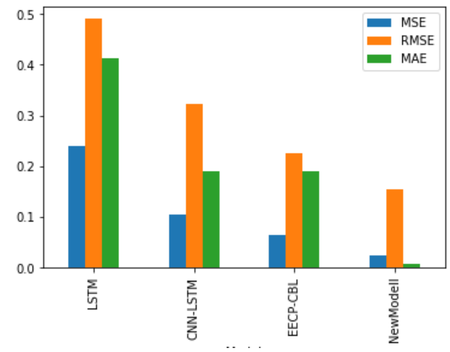

Fig. 6. New Model-1-Experiment-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MSE, RMSE and MAE.

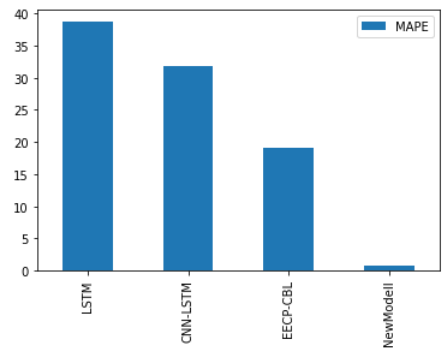

Fig. 7. New Model-1-Experiment-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MAPE.

training time, but the prediction time because a model is trained only once while it is used for prediction several times. For our model, the prediction time is reduced from 0.71 seconds for EECP-CBL to 0.18 seconds. However, this time is high for the LSTM (2.97 seconds) and CNN-LSTM (1.91 seconds) models. Consequently, the proposed model required the best training and prediction times to estimate future energy consumption.

b) Experiment 2: For the second experiment, the training set is formed by the first and second years while the third year is used for the testing set. Table III and Fig. 6 and 7 show that for this experiment our model reaches the best values of MSE, RMSE, MAE and MAPE which are respectively 0.023, 0.154, 0.008 and 0.841.

Moreover, referring to Table III, we observed that the proposed model was trained for 5.69 seconds and required 0.175 seconds for prediction. From Fig. 8 we can see that our model has spent the shortest time for training and for predicting.

c) Experiment 3: By modifying the training set (one year) and the test set (2 years), the results of the proposed model remain better than the existing models in terms of performance measures (Fig. 9 and 10) with the values 0.017, 0.131, 0.018 and 1.844 of MSE, RMSE, MAE and MAPE,

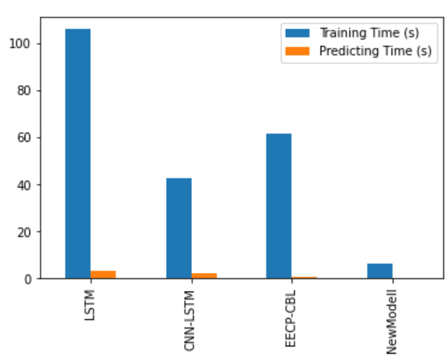

Fig. 5. New Model-1-Experiment-1 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of Training Time and Prediction Time.

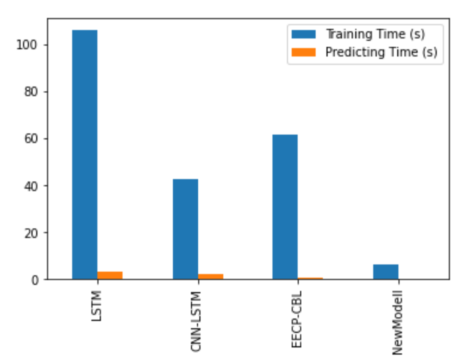

Fig. 8. New Model-1-Experiment-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of Training Time and Prediction Time.

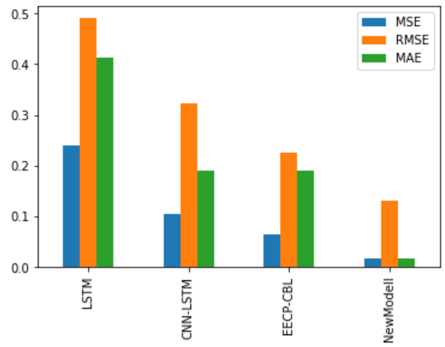

Fig. 9. New Model-1-Experiment-3 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MSE, RMSE and MAE.

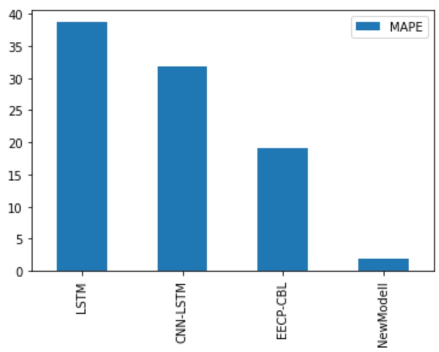

Fig. 10. New Model-1-Experiment-3 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MAPE.

respectively (Table III).

Also, we deduce from Table III and Fig. 11 that the proposed model has the shortest prediction training time.

d) Model-1 Experiments' Comparison: Fig. 12 compares the results of the three experiments to evaluate the proposed model. We see that the MSE and RMSE values of experiments 1 and 3 are similar while the MAE and MAPE values are slightly different. On the other hand, the values of the performance measures of experiment 3 are slightly different from those of the other experiments. Additionally, the training and prediction times of the three experiments are too close together. We conclude that our model achieves the best performance measures and the shortest training and prediction times, regardless of the choice of training and testing sets.

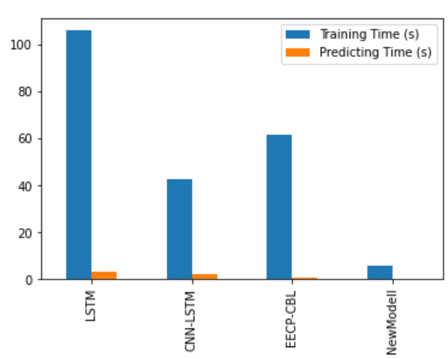

Fig. 11. New Model-1-Experiment-3 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of Training Time and Prediction Time.

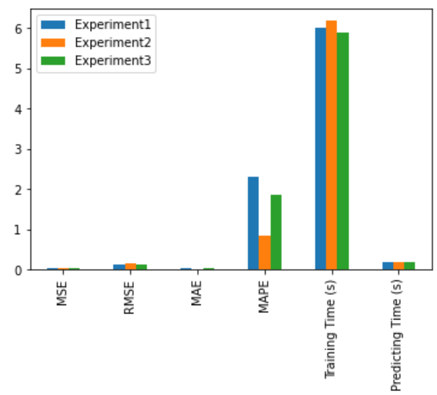

Fig. 12. Summary of New Model-1 Results.

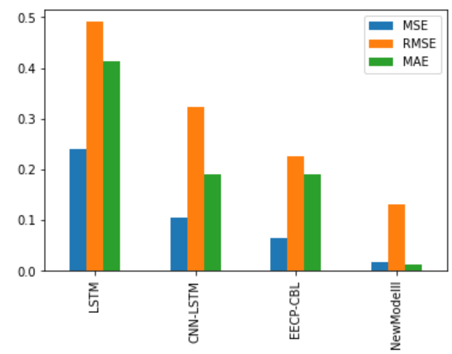

Fig. 13. New Model-2-Experiment-1 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MSE, RMSE and MAE.

TABLE IV. Model-2: Performance of the Experimental Methods

Model	MSE	RMSE	MAE	MAPE	Training time (s)	Prediction time(s)
LSTM	0.241	0.491	0.413	38.72	106.06	2.97
CNN-LSTM	0.104	0.322	0.191	31.38	42.35	1.91
EEPC-CBL	0.065	0.225	0.191	19.15	61.36	0.71
Exp. 1	**0.017**	**0.131**	**0.013**	**1.386**	**5.22**	**0.17**
Exp. 2	**0.023**	**0.154**	**0.008**	**0.841**	**5.69**	**0.17**
Exp. 3	**0.017**	**0.131**	**0.0122**	**2.552**	**4.81**	**0.16**

2) Model-2 Evaluation Results:

a) Experiment 1: The second proposed model also achieved the best values of the performance measures MSE, RMSE, MAE and MAPE comparing to the LSTM, CNN-LSTM and EECP-CBL models as shown in Fig. 13 and 14. All values are detailed in Table IV.

Similar to the previous experiments, Table IV and Fig. 15 show that our model spends the shortest time for training and for predicting.

b) Experiment 2: From Table IV, we can observe that the value of MSE is improved by more than 25% compared to the EECP-CBL model and the values of RMSE, MAE and MAPE are approved by almost 20% compared to the EECP-CBL model. Fig. 16 and 17 demonstrate that our model

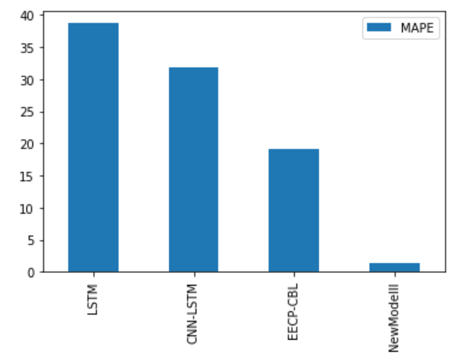

Fig. 14. New Model-2-Experiment-1 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MAPE.

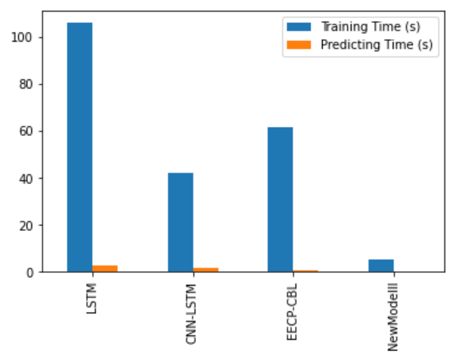

Fig. 15. New Model-2-Experiment-1 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of Training Time and Prediction Time.

achieves the best accuracy performance compared to other models.

Referring to Table IV and Fig. 18, our model achieves the shortest training and prediction time.

c) Experiment 3: Finally, the evaluation results of Experiment 3 are presented in Table IV. For the values of MSE, RMSE, MAE and MAPE, our model reaches better values than the improved EECP-CBL model. Fig. 19 and 20 show that our model has the best performance measures.

In terms of training time and prediction, our approach gives better results as shown in Table IV and Fig. 21.

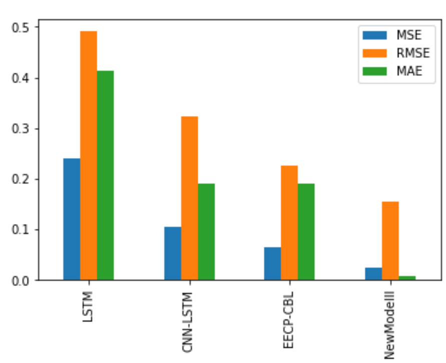

Fig. 16. New Model-2-Experiment-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MSE, RMSE and MAE.

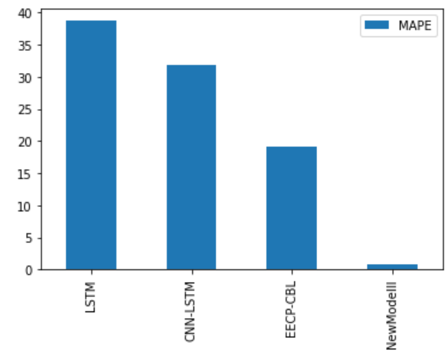

Fig. 17. New Model-2-Experiment-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MAPE.

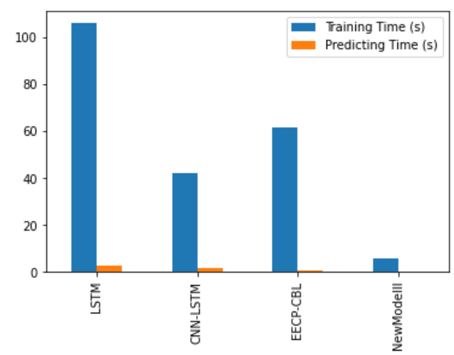

Fig. 18. New Model-2-Experiment-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of Training Time and Prediction Time.

d) Model-2 Experiments' Comparison: Fig. 22 presents a synthesis of the results obtained by the second model proposed in the three experiments. We can see that the values of MSE, RMSE and MAE are almost equal with a slight difference between the values obtained by the second experiment and the two other experiments. We also notice that the value of MAPE differs slightly from one experiment to another with the best value being obtained for two years of training and one year of testing. In terms of training and prediction time, the three experiments reach very close duration. Consequently, we conclude that our model achieves the best performance for all experiments. To conclude, for the two proposed models we

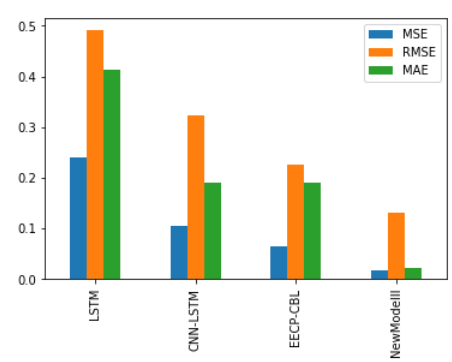

Fig. 19. New Model-2-Experiment-3 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MSE, RMSE and MAE.

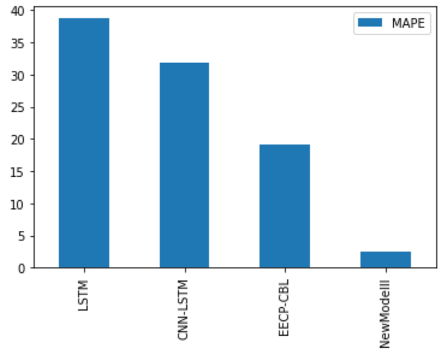

Fig. 20. New Model-2-Experiment-3 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MAPE.

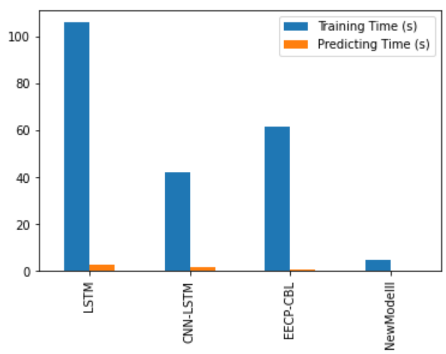

Fig. 21. New Model-2-Experiment-3 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of Training Time and Prediction Time.

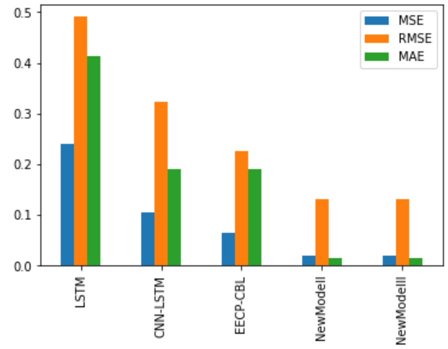

Fig. 23. Average of Model-1 and Model-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MSE, RMSE and MAE.

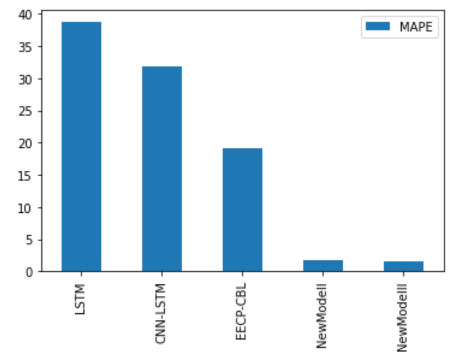

Fig. 24. Average of Model-1 and Model-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of MAPE.

calculated the average of the results obtained and compared them to those of the LSTM, CNN-LSTM and EECP-CBL models. The comparison of the MSE, RMSE, MAE and MAPE measurements is presented in Fig. 23 and 24. While Fig. 25 shows the comparison of all models in terms of training time and prediction time.

We observe that for the two proposed models reach the best values of MSE, RMSE, MAE and MAPE compared to the existing models LSTM, CNN-LSTM and EECP-CBL which proves the effectiveness of our model in terms of accuracy performance . Moreover, we studied the learning and prediction time of the proposed models in both models. The learning time of our models is equal to 70% of the best time obtained by the CNN-LSTM model. Moreover, our approach requires only 39% of the time required by the EECP-CBL model.

Therefore, we conclude that the results obtained from the new models significantly outperform the other models in terms of predictive efficiency. In addition, our models improve the training time, but most importantly, they deemphasize the prediction time. Therefore, the proposed models enhance energy consumption prediction results on the daily dataset derived

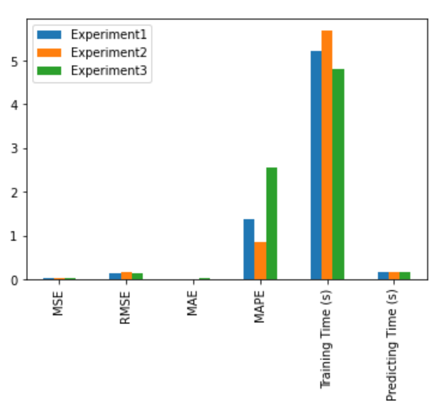

Fig. 22. Summary of New Model-2 Results.

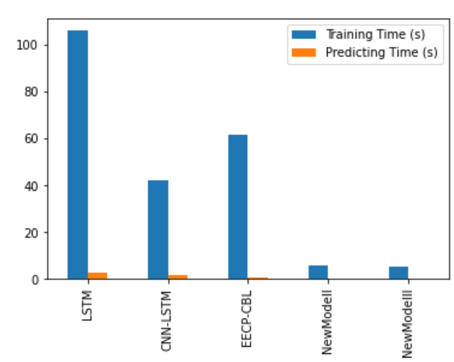

Fig. 25. Average of Model-1 and Model-2 *vs.* LSTM/CNN-LSTM/EEPC-CBL in Terms of Training Time and Prediction Time.

from IHEPC in terms of performance measures MSE, RMSE, MAE and MAPE and in terms of training and prediction time.

V. Conclusion

Since the demand for energy is growing more and more following the demographic and technological development, it has become imperative to manage and optimize the use of energy between consumers and suppliers. For an efficient energy management system, it is necessary to predict the future demand of users in energy which is a difficult target due to several factors. Various techniques based ML/DL for predicting energy consumption were proposed in the literature. However, most of them combine several models to be able to reflect temporal and logical dependencies between data. The focus of most researchers is how to make their models able to deal with these relationships by integrating recurrent mechanism. Nevertheless, the resulting models are often costly in terms of time and space. In this paper, we proposed a new research direction that deals with improving the structure of the input data rather than emphasizing on upgrading the model itself. The proposed model for energy consumption prediction is a simple 3-dimensional CNN that uses a new structure based matrices for the input data that physically reflects its logical dependencies. The experimental evaluation with the existing models LSTM, CNN-LSTM and EECP-CBL showed that our model outperforms existing ones in terms of MSE, RMSE, MAE, MAPE and required time for training/testing.

In a future work, we will integrate this model into the intelligent A-RESS system proposed in [41].

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