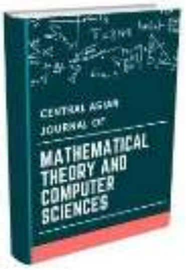

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Article

Long-term Energy Forecasting Methodologies: Review and Discussion

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Abstract: Due to the development of human activities, energy demands are rapidly variable nowadays; these changes need to be tracked by the energy producers and suppliers. Adding new generation facilities is considered costly and time-consuming for the electrical Energy. Therefore, it is important to forecast the demand growth for the long term, in which a new facility is established to fulfill the presented demand. Further, the guidance of the capital's enhancements in the sector is also highlighted. However, the current paper concerns the long-term load forecasting methodologies, which are presented and discussed precisely. The accounted methods are classified according to availability, so the most available methods are classified first, then each category is listed and explained. Another vital factor encompassed by the former suggested methods is analyzed accurately, starting from the input dataset and the selected input parameters and their effect on the obtained results, then the comprehended periods by the input dataset and ending with the performance indices that are used to measure the performance of each method. Furthermore, a couple of significant points are concluded: The first is the necessity for a generalized data set to be used as a test bench for the suggested methods. The second one is the selection of the proper performance indices to measure the performance.

Keywords: long-term energy forecasting, machine learning, deep learning, statistical models, performance metrics, energy planning

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1. Introduction

Recently, energy forecasting is considered one of the most economical solutions to identify when and where the highly investing budget resources need to be interrupted for governments and energy industrial companies. The energy planet is one of the costed and long-time designs and implementation structure establishments because it needs to influence other planets linked alongside supply. Thus, short-term forecasting allows operators to manage which planet stops and which works in partially-fully load. In contrast, the long-term predicts the demand for Energy, which is a grant of economic cash and satisfies the sustainability of its flow. Overinvesting in the mentioned side will not only enhance unnecessary costs but also have a high environmental consequence due to the high Carbon Dioxide and other greenhouse gases. Further, the insufficient supply to the demand plays a crucial role because it will cause the residential building to undergo load shedding and blackout, a highly negative economic outcome.

Researchers have begun establishing models for the past 20 years. Consequently, various models came to the scene, each of which had its role as a candidate or was selected for experience according to certain categories. The availability and quality of the data that structured the model crucially influenced the selection of its methodology. Many models are implemented in many types of methodologies; this research categorized them into specific types of methodology and give them a brief in each category. This research may be considered as the first step on a long road for all the researchers that need to take

The presented research consists of six parts: The first part is the introduction, the second is the methodology types used by the researcher, and the definition of the major models with the period of the data set and its location. The third part is the data set and input features involved in designing models. The fourth one is the performance measurements that are used by the researchers and how to find the best results. The fifth part discusses the previous parts. Finally, the last part is the conclusion of the current research.

2. Materials and Methods

2.1 Methodologies and processing

Each problem has specific ways or steps to be solved, LTEF problem is thought of as an exemplified one. Consequently, there are three major steps to solve the presented problem as the figure shows.

2.2 Data gathering and engineering

Generally, LTEF dataset has several sources that need to be gathered and uniformed in the same periods or sampling time [1]; the dataset may be univariable or multivariable depending on the availability of this data and its complexity; it also might be divided into two types: Data with the same file, which is the well-known ones, or with the same dataset. To enter the second process of problem-solving with a single tool of programming or multi tools like: MATLAB [2], SQL [2], or Python,with many types or frameworks like: Sklearn [3], TensorFlow [4], PyTorch [5], Pandas [6], Numpy [7], and Matplotlib [8], with various versions of all mentioned libraries.

2.3 Methodologies evaluation types

Depending on the data, Forecasting problems have two ways to predict model(s): the first way is qualitative forecasting, which takes place when there is no previous or any data to build the model(s) on, which is not the scope of the accounted paper. The second way is quantitative forecasting, which concerns the availability of historical data, which is the main scope or concern of the presented paper. [9]

However, in quantitative forecasting and due to the complexity of the data that is evolved in the long-term analysis, which is, often the time series. The methodology of the mentioned data obeys the statistical algorithms that find the best solutions for the time-series data. In general, figure (1) will concentrate on some types of forecasting problem-solving.

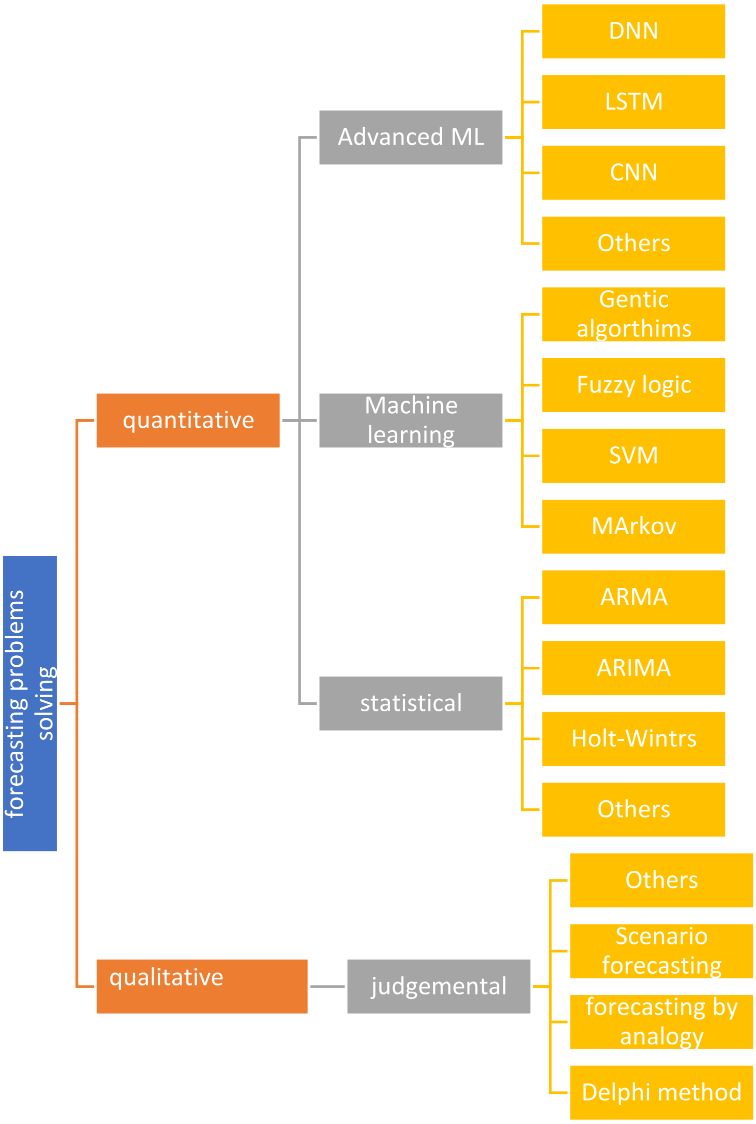

Fig 1. Forecasting problem solving

Computing power definitely has played a vital role in static disappears gradually from the Long-Term Energy Forecasting LTEF, with high complexity and due to the uncertainty, nonlinearity, and chaos, Artificial Neural Network ANN and later Deep Neural Network DNN demand the primary application of research's directions. For these reasons, we shall divide the methodology of solving as

1. Statistical
2. Machine learning
3. Advanced machine learning

3. Results

3.1 Statistical

One of the most important models that can be entitled Autoregressive Integrated Moving Average ARIMA, which is the generalization of the Autoregressive Moving Average ARMA or integrated ARMA that is used in the univariate time series analysis

AR: forecasting model by using the past or old values of the output in its estimation as this equation (2.1)

$$Y_t = C + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t \tag{2.1}$$

Where ε_t is the white noise.

MA: forecasting model by using the past error values in its estimation as this equation (2.2)

$$Y_t = C + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-\mathrm{q}} + \varepsilon_t \quad (2.2)$$

I: The integrated part is added to make the time series stationary.

So, the non-seasonal ARIMA can be in an equation (2.3)

$$Y_t' = C + \emptyset_t Y_t' + \emptyset_{t-1} Y_t' + \emptyset_p Y_P' + \cdots \emptyset_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-\mathrm{q}} + \varepsilon_t \quad (2.3)$$

Where the difference is the reverse of integration.

ARIMA model is written in formula (p,d,q)

Where p=substitute as the order of the autoregressive part

p substitute as the order of autoregressive part

d substitute as the order of differencing part

q substitute as the order of moving average

[9]

The earliest researcher's implementations of the LTEF were portrayed in statistics or as a significant part of the solution's process. At the same time, the main issue with other techniques was considered a minor part.

In 2012, Rallapalli and Gosh forecasted the peak demand in India. They implemented their work wit ARIMA and Multiplicative Seasonal Auto-Regressive Integrated Moving Average MSARIMA between 2002-2011, lasting two years.[10]

Classical multiple linear regressions in [11] deal with probabilistic forecasting; they use weather and other variables to solve their problems.

Iranian and US data were introduced to forecast energy consumption with a multiple regression. With ANN and improved with Particle Swarm Optimization PSO, with an observation for 20 years 1967-2007. [12]

South Africa forecasted peak electricity demand; they deduce the Seasonal ARIMA SARIMA and Time Series Regression- Threshold Generalised Autoregressive Conditional Heteroskedasticity TSR-TGARACH models for LTEF for 10 years between 2000-2010. [13]

Between 1970 and 2015, Turkish energy consumption was utilized by [14]. Using only ARIMA, they predict the LTEF until 2040.

ARIMA and non-linear NARIMA have been conducted as models to predict LTEF from 2015 to 2040 using data from 1990 to 2015 for the Iranian energy sector.[15]

The previous research [16] introduced the rolling Metabolic Grey Model MGM, MGM-ARIMA, and Non-Linear NMGM for China and India LTEF. They implement three models using three techniques and find the best way to deepen their measurements.

A hybrid approach is considered to get LTEF in Turkey's energy sector, ARIMA, and Support Vector Machine SVM time analysis of data between 1970-2017.[17]

Finally, LTEF of Kuwait with Prophet and Holt-Winter models with data between 2010 and 2020.[18]

Certain researchers use statistics as comparative models to find the best solutions with other approaches.

3.2 Machine learning

The most crucial machine learning ML algorithms are utilized in this science section. LTEF researchers also combined ML with statistic algorithms in many research papers as a comparative study. They might be classified as a hybrid, while most recent research uses the statistical, but they tend to recent algorithms won in the race of measurements. The ML is divided into primary research that does not apply deep learning algorithms to elect a model and secondary research that applies it.

In 2003, Fu [19] applied Functional-link Net FLN and ANN with Wavelet network as a dynamical model to improve its accuracy. The historical Australian annual energy data from 1996 until 2000 was served.

Swarm intelligence and Turkish data from 1979 to 2005 established LTEF until 2025. PSO, Ant Colony Optimization ACO has been confirmed as a model that could be implied in prediction estimation.

Greek LTEF prediction was introduced in [20]. With Multi-Layer Perceptron MLP, the Author predicts the energy consumption model until 2015 with less error in linear regression of the same data.

The Adaptive Network-based Fuzzy Inference System implies that ANFIS has been widely used for forecasting. [21] forecast electrical Turkish load between 1999 and 2025 with a model that merges fuzzy logic and ANN.

Genetic algorithms such as (the Genetic Expression Programming GEP program are used) in [22]. Chromosome mutation used for widening population and PSO, CSA and BSA for the optimization has been involved in this research to predict a model for five southwest Asia countries' electrical consumption.

For millions of houses and three datasets given big data mining, the UK, Canada, and Irish social data Archives [23] analyze the mentioned data with SVM and MLP algorithms and find energy consumption patterns. This unsupervised forecasting model is also recognized.

AS [21] introduces ANFIS for LETF, [24] also utilizes the same work with different datasets. They used University Technology Malaysia for 60 months from 2007 to 2011.

ANN is also used as a comparative model implemented in MATLAB. Although both can behave dynamically, ANN has won with the best performance.

ANFIS and MLP are also used in Bahrain LTEF peak load [25]. They used datasets between 1992 and 2011 with different features to predict the electrical energy needs of GCC countries.

Australian long-term demand forecasting using ANN and the deep neural network has been implemented. The data set is between 1999 and 2013

The Jaya algorithm was intended to constrain the SVR weights and GA in [26]. The ϵ-SVR and ν-SVR with ACO and PSO are also used to optimize the best testing and verification data.

Compositional techniques in [27] estimate the dynamic change in China's consumption energy structure. They used many methods to establish their model: Gray Model GM, Direct Gray Model DGM,….ARIMA, and even linear regression. All the sector data on Energy have been added to the period between 1980 and 2017 to produce a forecasting model until 2030.

A hybrid technique has been developed. This compositional method involves the PSO with Support Vector Regression (SVR) to investigate the LTEF of Iran's national grid—the peak load and Energy data between 1991 and 2016. The Authors [28] also compared ARIMA with another technique, ANN. However, they found that ARIMA is sensitive to random and seasonal data, and the error was minimal in the proposed PSO-SVR technique.

3.3 Advanced ML

We need these parts to focus briefly on the technique or method used in this part.

3.3.1 Recurrent Neural Network RNN

The Recurrent neural network is ML network that not only outputs depend strictly on the input features but also on the previous output. Two examples that explain to.

3.3.2 Long Short-term Memory LSTM

Long short-term memory, introduced by [29], combines long-term and short-term memory, and it's controlled by adaptive gates (input, output, and forget gates); LSTM adds to their memorizing function, and it can store the temporal state of the network. Each gate has a function, input and output gates manage the input and output respectively while the forget gates manage which parts of information remember and which forget.

The benefit of LSTM is to reduce the vanishing gradients problem that appears in the DNN

This is done by controlling the parameters of the gates mentioned above. Figure (2) will give us the simple one cell of LSTM

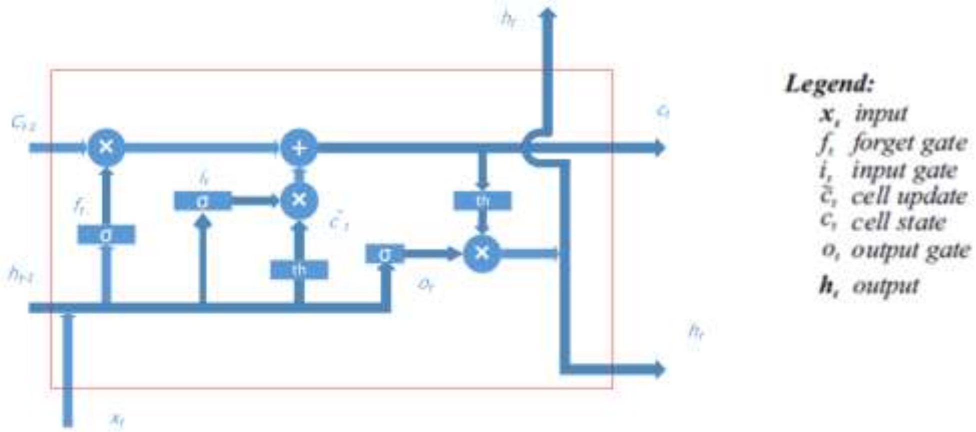

Fig 2.LSTM cell

Where the cell's function can be managed by the equations below

$$f_t = \sigma(W_f \cdot [h_{t-1}.X_t] + b_f \quad (2.4)$$
$$i_t = \sigma(w_i \cdot [h_{t-1}\,.x_t] + b_i \quad (2.5)$$
$$c_t = f_t \otimes c_{t-1} \oplus i_t \otimes \tanh \quad (w_C \cdot [h_{t-1}] + b_C) \quad (2.6)$$
$$\sigma_t = \sigma(w_o \cdot [h_{t-1}.x_t] + \ b_o) \quad (2.7)$$
$$h_t = \sigma_t \otimes \tanh(C_t) \quad (2.8)$$

3.3.3 Gated Recurrent Unit GRU

The gated Recurrent Unit, introduced by [30], has fewer parameters of LSTM and is simpler and can have the same purpose as LSTM; it has two gates (reset and update). Figure (3) highlights a schematic diagram of GRU

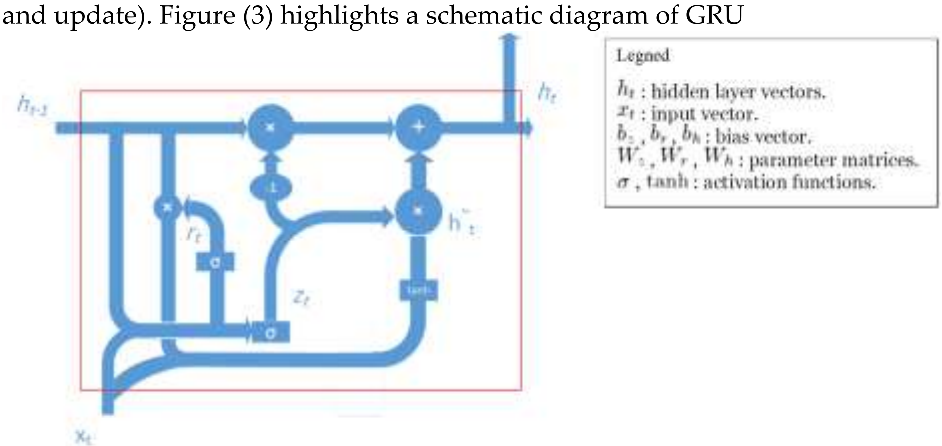

Fig 3.GRU cell

Where the equation bellow can manage the cell's function

$$z_t = \sigma(w_z \cdot x_t + U_z \cdot h_{t-1} + b_z) \quad (2.9)$$
$$r_t = \sigma(W_r \cdot x_t + U_r \cdot h_{t-1} + b_r) \quad (2.10)$$
$$\tilde{h_t} = \tanh(W_h \cdot + U_h \cdot r_t \cdot h_{t-1} + b_h) \quad (2.11)$$
$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h_t} \quad (2.12)$$

Most problem-solving methods deduce the computational speed that has grown in recent years, which leads to all these techniques that need high computational speed and more memory usage. These techniques are surrounded by Deep learning algorithms (GRU, LSTM, CNN, attention).

We sort these techniques depending on their complexity, from the simple to the complex.

IN GRU [31] and [32] have built their model using stacked in the latter or combinational with CNN in the first one. [31] use data set of Individual Household Electric Power Consumption and Appliances Energy Prediction, IHEPC has nine features date, time, voltage and global active power and others measured between 2006 and 2010 in a residential house in France for one-minute resolution. Meanwhile, [32] uses German datasets for weather and energy generation.

Early researchers [33] built their work on LSTM and used sequence to sequence S2S (encoder and decoder). This is a one-minute-resolution dataset of power consumption between 2006 and 2010.

Later, [34], they used an improved sine cosine optimization algorithm to enhance the LSTM by Improved Sine Cosine Optimization Algorithm (ISCOA-LSTM). The data set for two years in 30-minute resolution, with many features.

Bi-directional LSTM with CNN in [35]has been used to improve the prediction of electrical energy consumption using the IHEPC data set for global active power.

PSO with CNN and LSTM was used by [36] to forecast household electric power consumption. With a one-minute resolution, they predicted a 60-minute energy consumption prediction.

Also [37] has used particle swarm and add the GA to tune hyperparameters for load prediction and forecasting. The data set used in this research is from the French metropolitan for years between 2008 and 2016.

Switzerland data set for four years (2015-2018) in [38] with UNI-LSTM and BI-LSTM only, with disparate structures, different hyperparameters, and comparable with the SVR model.

Similarly, [39] uses LSTM instead of ANN, ARIMA, SVR, and MLP models for monthly residential-sector electricity forecasting. They use a 22-year data set from 1991 until 2012 with social, weather, and electrical demand input variables.

[40] uses the dual-stage of LSTM (dual-stage attention) to predict energy demand on a data set of three-year-old daily consumption households in Shanghai with 15 weather parameters for model training features.

LSTM outperforms other models in [41], such as ARIMA and ANN, which are the data set sources of 12 households for 2 months in 2018.

Adding singular spectrum analysis to parallel LSTM enhances the investigation of the instability of dependency on long-term data. This is found in [42], which uses UK household data between 2012 and 2017.

Electricity demand forecasting with an Irish dataset between 2013 and 2018 in [43]. The authors use LSTM and SVM models only.

[44] used Random Forrest RF with LSTM in the total energy consumption data set of South Korea between 1965 and 2020. They found that the RF model was more accurate in some periods, and LSTM was best for others. This happened when the data had a discrepancy of the time series in which the AI was the satisfied solution.

Under false attack, the electrical load is forecasted using autoencoder LSTM [45]. In addition, they used CNN as a comparable model to investigate the proper model for cyber-attacks. Tabriz, Iran's data set, was used for the period between 2017 and 2019.

3.3.4 Convolution Neural Net CNN

Convolution neural net, introduced by [46]. Consists of three layers (convolution, pooling, and fully connected network) or is called by Lenet-5. Most uses of CNN were in image and video recognition, image segmentation, image classification, and time series forecasting. Figure (4) shows the architecture of Lenet5.

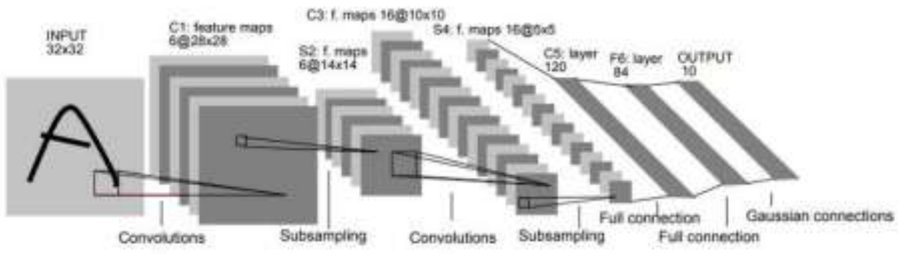

Fig 4. The architecture of Lenet5 when used in character recognition [46]

Its filter is helpful for extracting features from the input data of different enhancements in the CNN we can find in [47].

One of the first author's works in CNN is [48], which they used for four-year residential houses with a one-hour resolution measured between 2006 and 2010. They concluded that SVM ANN and LSTM, as comparable results, are not highly better than CNN and candidates as good alternative models in the future.

Modifying the CNN to work appropriately with time series, Temporal Convolution Neural Network TCN suggested by [49], the developments were done by making the output of the network the same as the input, and also by performing the casual convolution rather than the stander convolution in order to prevent the leakage of the information from future to the past. The data set was the national electrical energy demand in Spain for the years: 2014 - 2019.

In [50], the CNN was used to find the weather feature input as pre-filters which will feed to another ANN network, The used French grid was for forecasting the Energy for the period back to 2012 and the weather image used is from 1 October 2019 tell 30 September 2019.

Multi-head and multi-channel CNN outperforms the invariant CNN [51]. Authors study the LTEF via socioeconomic factors in Florida –USA. This paper deduces many features that evolved socioeconomically like employment, unemployment rates, visitors…etc for the years: 2010 - 2018.

The same technique above but combined with LSTM [52] has confirmed better performance. The authors also compare their results with other models as usual like LSTM and just CNN, they use Panama data set of peak demand between 2004 and 2019.

3.4 Data sets and input features variables

As far as has been studied, there is no energy consumption for a specific area similar to another one, differences come to the scene according to certain parameters such as: Social construction, population Gross Domestic Product GDP, weather conditions, and it might also be human activities and behaviors. As the mentioned reason suggests, the data sets will differ from one research to another, so that it results to the model to be different. Consequently, it cannot be used for establishing a comparison between two or more studies.

Some authors use the same country (IRAN) with different periods of time like [12], [15],[28], [45].Also [35]and [31] deploy their models with (IHEPC) data set

Data sets may have univariate data on Energy, peak consumption, electrical load, and the like. This happened in earlier research with ARIMA and statistical calculation. While later researchers use additional two types of correlated features to enhance the model with more input features

3.4.1 Weather conditions

The most common weather condition applied is the temperature stuff such as: Average temperature, maximum temperature, minimum temperature, daily, or hourly. Some authors [40] use 15 features like wind speed, while others use chicness data [45] for weather conditions.

3.4.2 Social and economic variables

Recently, social and economic features have taken place in the research field. This happens when the data of the deep learning various features are added flexibly. GDP appears in 30% percent of researchers' surveys, while the population appears close to this percentage (28%). Other authors vary or add more variables like: Export, import, income, and other social and economic variables.

3.5 Performance measurements

"If you can't measure it, you can't manage it is", a famous quote by Peter Drucker founder of modern management.

The importance of performance measures takes the winning cards in every research, all eyes will be directly focused on the results of the measurements and how much difference between them, because these measures will give the judgments word of which methodology is the best. On the other hand, many authors [53], [54], and [55] divide the measurements based on how the comparison is made between: The forecasting and previous actual reading (error) as following.

3.5.1 Scale-dependent measure

It is useful when we use the same data sets but with a different methodology. While it's not advisable for the data set to have a different scale. The best example for these measures that based on a square or an absolute error.

Mean square Error (MSE) = mean (e^2) (4.1)

Root Mean Square Error (RMSE) $=\sqrt{MSE}$ (4.2)

Mean Absolute Error = Mean $(|e_t|)$ (4.3)

In our review, RMSE and MSE took the third and fourth most popular used as shown in figure (5). Both of them are highly sensitive to the data outlier.

3.5.2 Scale-independent Percentage error measures

The most commonly used measures, where the percentage is

$P_t = 100\, e_t / Y_t$ (4.4)

When Y or the output is equal to zero, the percentage P is undefined, or even the output close to zero also makes the percentage skewed. Another drawback of this type is that asymmetric measures happen between the positive and negative values, which tend to penalize the positive values more. These drawbacks can be solved by good preprocessing (removing zero output) or using absolute errors for the latter. [56].

These measures examples like:

Mean Absolute Percentage Error (MAPE) = mean $(|P_t|)$ (4.5)

Mean Square Percentage Error $mean(P_t^2)$= $mean(P_t^2)$ (4.6)

Root Mean Square Percentage Error (RMSPE) = $\sqrt{mean(P_t^2)}$ (4.7)

1. Relative error measures

   When use $r_t = {e_t}/{e_t^*}$ where is the relative error and e_t^* is the denotation to the forecasting error which is not used in our survey also measure with the relative measures are not used in this survey.

2. Coefficient of Determination

   This measure is the rationality between the dependent and independent variable

   Denoted as R^2 (R square) introduced by Wright, S. (1921). "Correlation and causation"

   In our survey, R^2 is the Fifth rank of using it can be written as :

   $R^2 = 1 - \frac{MSE}{MST}$ (4.8)

   Where the MST denotes Mean Square Total = $\frac{1}{m}\sum_{i=1}^{m}(\bar{Y} - Y)^2$ (4.9)

   $\bar{Y} = mean$ (4.10)

Some authors [57] conclude that R^2 is directly links with the regression algorithms, if it has a negative value, It will be poor performance, while has the best when it's between 0 and 1. The drawback is that the negative value does not proportional to how bad values it has, it mean that -0.5 does not worse the -∞ and vice versa.

In fig(5) we sort the using the more influent measure used in this paper and we widen the scope of researches that not used on specific long-term , we add mid and short term also ,because these measurements are not time independent scope like ..[58],[11],[59],[60],[61],[34],[31],[62],[63],[64],[65],[66],[67],[32],[68],[69],[70]. The other measures were not mentioned, because they will only use them in a single or two and will give an index at the end of the paper for the acronyms and its equation. On the figure below (fig5), they represent all mentioned performance measures with its recurrence in the vertical axis while in the horizontal axis the name of the performance. Colors represent the reference number that used this measure.

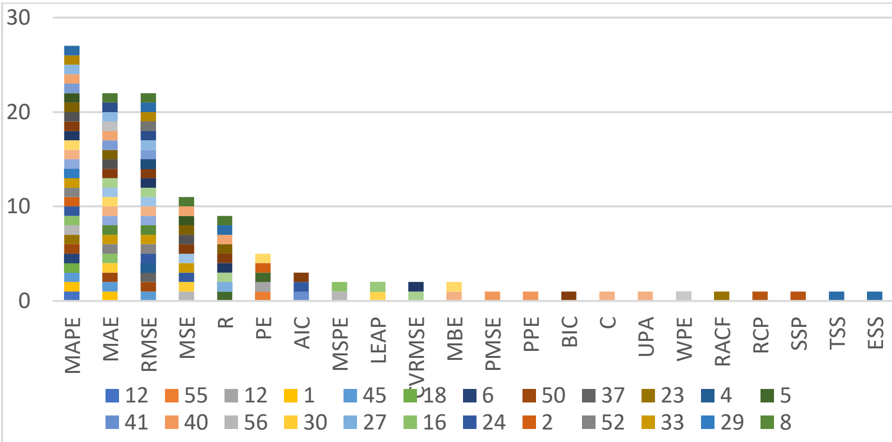

Fig5. Representation used measurement of performance types

4. Discussion

4.1 Methodology discussion

For the ARIMA model, it will be successful if there is a univariate mid-number, sample data set and work for non-stationary time series, if not we can use another way like Vector Autoregressive Moving Average (VARMA). Discontinuity of the data set is also a reason to avoid implementing the ARIMA model. Multivariate model should be implemented in another model design

The sample of the high data with ARIMA needs more computational resources due to the integration parts of the ARIMA equation. According to the reasons mentioned above, authors shifted towards the ANN methodology

To avoid discontinuity and to use multivariate time series, preprocessing of the data set must accomplish before driving the data set for the model training and other steps. Hence, removing missing values and the normalization are the major principles and techniques for all the time-series analysis and modeling establishment that deduces data-driven methodology. So, the data-driven models work on their specific data set, changing the data set (for another region, or another time-space), which will reduce the model's accuracy.

Overfitting is another issue that affects the model design; it happens when the model learns too much. Since ANN and DNN are black boxes based on the model design, so it is barely hard to modify or identify what is best modifying parameters that are needed to vary. Thus, with a huge dataset and multivariate, DNN may use to enhance the model generation with RNN (LSTM, GRU). Since the major concern of

CNN is the vision and image, processing CNN tested in forecasting and confirmed significant results. In brief, all NLP and RNN Deep learning techniques have a significant model design that leads to encouraging forecasting results.

4.2 Data input features discussion

Recently, various authors tend to increase correlated features, due to the possibility of amplifying the accuracy of the forecasted model design. The DNN helps with the mentioned process and works well when the training data is huge.

However, most of the acquired features between the weather and economic reading, as mentioned in the specific sector of the research.

4.3 Performance measurements discussion

Nowadays, the robustness of computational power adds more powerful and various ways to measure the accuracy of the forecasting model and how the actual data vary with predicted data. The absolute percentage error (MAPE) is the best way to measure the error, while the (R2) is a significant measurement used in recent research.

The other measurements that were not included in the accounting research concern the computational power itself, for instance: the implementation time, iterations number, type of computer, etc. These measures are not related to the data or the problem; they concern the computer that is used for the modeling. So, varying the computer will vary the measurements.

5. Conclusion

In this paper, long-term energy forecasting methods are reviewed and discussed, so specific results were concluded: One of the most critical issues that prevent researchers in the presented area from doing reliable comparison and analysis is the lack of standardized data set input that can act as a test bench.

Another issue that is discussed is that online cloud or even offline deep learning applications are widely spread nowadays, in which online applications can easily perform a huge data set model analysis and design with multi-input features. While for single features and moderately large data sets, ARIMA is specified for only comparable studies with deep learning model design.

In addition, performance measurements are easily concluded as side effects of a high computational revolution.

Big data and IoT systems generate huge data sets that can only be handled by deep learning systems. These systems ignore the classical ways to investigate forecasting models. The extracted data from these systems contains social and environmental data that, when added to the energy data, make it difficult to use hybrid systems, too.

During the mentioned process, security of the power system is the interested line that most researchers need to focus on, in order to prevent attacks on the data, and find developed models that distinguish between real and fake generated data by the attackers.

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