Electricity Power Consumption Forecasting Techniques: A survey

Aman Gupta[a]*, Dr. Meenu Chawla[b] and Dr. Namita Tiwari[c]

[a]*Artificial Intelligence, Computer Science Engineering Dept., Maulana Azad National Institute of Technology, Bhopal, India, e-mail: Aman273g@gmail.com*

[b]*Computer Science Engineering Dept., Maulana Azad National Institute of Technology, Bhopal, India, e-mail: Chawlam@manit.ac.in*

[c]*Computer Science Engineering Dept., Maulana Azad National Institute of Technology, Bhopal, India, e-mail: Namita_tiwari21@rediffmail.com*

Abstract: For utility companies, load forecasting is critical in all areas of system health management, including but not restricted to electrical grid maintenance, power system operation, rate design, and financial planning. To avoid an energy crisis, variable electrical load and ever-increasing load demand must be forecasted. The ability to effectively manage power usage was achieved by accurate prediction. This study will offer a review of recent electric consumption forecasting approaches in the context of various power consumption forecasting applications. This study provides a survey of works on energy forecasting published between 2017 and 2020. This research focuses on a complete assessment of existing approaches for power consumption prediction, as well as a comparison of different models based on the (three) methods, prediction time period, numerous input features, various performance metrics (such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) metric etc.), datasets, etc. The findings, on the other hand, demonstrate that the researchers' selected machine learning algorithm, different metric assessment, dataset size and input features may impact the accuracy of the model created.

1. Introduction

Many professions find time series forecasting to be a difficult task. Stock exchange courses or indices are forecasted in finance, while data processing professionals forecast the flow of data on their networks [1]. Predicting electricity demand is a critical element for power sector planning and development as it helps to match the future power demands of a variety of sectors consuming electricity. To have unified growth in all sectors of the economy planned load growth in industrial, agricultural, domestic, and other sectors is required, and infrastructure in various sectors of electricity consumption must be planned in order to drive the total expansion of the economy in a reasonable manner [2].

Because of the growing deregulation of the energy market, it is more important than ever for utility providers to produce stronger load forecasts. Electric energy storage is either expensive, inefficient, or impracticable. Furthermore, the demand for and supply of power must always be balanced [8]. Because modern smart meter technology allows for the collection of a large quantity of relevant data, consumption forecasting has a substantial impact on smart grid applications [3].

Power load forecasting is critical in the capacity planning, scheduling, and maintenance of power systems, along with end-consumer awareness of observing their consumption pattern and bills in real-time [18]. Based on the time period of forecast, the electric power consumption prediction process is classified into three types short, medium or mid, and long-term predictions [4, 5].

• Short-term prediction: The time frame for short-term prediction ranges from a few hours to a day or a week ahead. It strives for economic dispatch, optimal generating unit commitment, power distribution, and load dispatching, as well as real-time control and security evaluation.

• Mid-term prediction: The time horizon for mid-term forecasts ranges from a few weeks to a few months. The goal of this form of prediction is to keep the system running by acquiring energy and settling prices so that demand and generation are harmonized.

• Long-term prediction: Long-term predictions range from a year to 10-20 years ahead. Its goal is to plan system expansion, including generation, transmission, and distribution. This forecast may also influence the procurement of new generating units.

Electric power consumption prediction remains a difficult issue due to the nonlinearity and uncertainty of different elements such as consumer behavior, weather conditions, economic variables, geographical factors, and other random effects [3].

The determination of sufficient and essential information for a decent prediction is a common challenge in the construction of credible forecasts. Forecasting will be bad if there is insufficient information; similarly, modeling will be difficult or even distorted if the information is irrelevant or redundant [1].

If a utility that is generating 10,000 MW of capacity reduces forecasting error by 1%, may provide a profit of $1.6 million annually [22]. Aside from economic savings, using less fuel would result in less pollutant, which would not only save raw materials but also benefit the environment [11]. The issue of carbon dioxide (CO_2) emissions is inextricably linked to a country's modernity. Because electricity generation is heavily reliant on fossil fuels, it is one of the major contributors to CO_2 emissions. Producing electricity in response to demand will help to reduce CO_2 emissions [6].

Forecasting energy consumption is a multivariate time series problem including multiple variables that influence power usage. The variables change depending on the user's usage habits and have an impact on power consumption [7].

To generate these three different sorts of predictions for diverse objectives, a wide range of prediction models have been developed and employed.

Many methods which are not working well for mid-to-long-term forecasting can work well for short-term forecasting by providing better results. Before using predictive analysis, it's important to understand the limitations of each method. Electric power consumption can be predicted using one of three ways based on the abovementioned prediction classifications:

• Statistical-based methods (ARMA, ARIMA, ARIMAX, SARIMA, Exponential Smoothing (SES), VAR)

• Machine Learning methods (LR, DT, RF, MLP, SVR) and

• Deep Learning methods (DLNN, CNN, RNN, LSTM, DELM)

Short-term forecasting was first done using statistical techniques such as time series and regression analysis. Later, artificial intelligence-based approaches such as fuzzy logic, artificial neural networks (ANNs), multi-layer perceptrons, support vector machines, and more emerged. Following that, machine learning methods were used, and ML-based approaches to prediction analysis were documented in substantial literature research. However, recently, the vast majority of researchers have proven algorithms based on deep learning for accurately predicting power consumption [3].

2. LITERATURE REVIEW ON STATISTICAL BASED METHODS

Hung Nguyen et al. (2017) [8] Proposed ARIMA and SARIMA models using observations between 2002 and 2015 (14 years data) taken from regions of Texas provided by ERCOT for short-term forecasting (6 days ahead). The goal of this study was to extract the random components of time series from the deterministic components of the dataset, such as cyclicality, seasonality, and trend, and then use the process of ARMA to build models. Because it allows for unpredictability in the seasonal pattern, the SARIMA model provides a superior match to time series data in the research. Mean Squared Deviation (MSD), Mean Absolute Deviation (MAD), and Mean Absolute Percentage Error (MAPE) are used as performance metrics. Different length of input data is used, like for 14 years length, MAPE is 9.13% for ARIMA and 4.36% for SARIMA. PACF i.e. Partial autocorrelation function and ACF i.e. Autocorrelation function represents the limits of ARIMA and SARIMA and represents the correlation between observational records of the same time that have not yet been considered.

Kantanantha et al. (2017) [9] proposed decomposition models (additive and multiplicative) Holt-Winters models (additive and multiplicative) for long term load forecasting taking consumption data set from the Electricity Generating Authority of Thailand (EGAT) and other input features like cyclical, seasonal, trend, irregular factors are considered. The monthly power consumption dataset from January 2010 to December 2014 is considered to predict monthly electricity demand from January 2015 to December 2015. To reduce the cost of imported coal inventories, demand predictions will be utilized for estimating the imported coal quantity orders to be placed. As a performance metric, Mean absolute percentage error (MAPE) is considered, and randomized complete block design (RCBD) is taken for accuracy comparison. All models' predicting accuracies are not substantially different. Still (with MAPE of 1.66%), because the seasonal and trend variations of this time series remain unchanged over time, the gathered power demand data of time series do not display clear continuous seasonal variation, and because of its simplicity, we consider the multiplicative decomposition model. Ordering costs, holding costs, and inventory costs are all reduced by 9.81%, 39.33%, and 14.84%, respectively, with the proposed order amount of imported coal.

S.Hadri et al. (2019) [10] using EEBLab testbed's real data set for electricity consumption (collected every second) with date and time as other features, proposed XGBoost, RF, ARIMA, SARIMA, and LSTM for predicting occupancy and controlling the appliances in a smart building. Root Mean Squared Error (RMSE), the Mean Absolute Percentage Error (MAPE), Mean Percentage Error (MPE), the symmetric Mean Absolute Percentage Error (sMAPE), Mean Absolute Error (MAE), the Mean Absolute Scaled Error (MASE) are used as performance metrics. With the least sMAPE of 4.33, XGBOOST beats other techniques, particularly in short-term forecasting. The sMAPE for RF, ARIMA, SARIMA, and LSTM models are 26.56, 22.84, 23.19, and 25.99 respectively. XGBOOST model provides not only higher accuracy but also better performance considering execution time. This approach is most suited to dealing with time-series volatility and is least affected by extreme values.

Kiani et al. (2019) [11] for short-term load forecasting introduced function-on-function linear regression approach taking the Pennsylvania, New Jersey, and Maryland (PJM) electricity market load data considering training data from December 2008 to November 2016. A single cluster may be expressed as (season, Day), with season having 4 distinct values and day having 7 different possibilities. Because of electric load data's daily changing nature, cubic B-splines were chosen to depict them. As a performance metric Mean absolute percentage error (MAPE) is taken and ARIMA model for comparison. The results show that treating the utilities individually when doing load forecasting and then aggregating the results is preferable to running a single analysis on the whole data, for example: for Winter, Monday, MAPE values are 2.257 (Aggregate), 2.727 (Overall), 8.976 (ARIMA). When compared to a standard ARIMA model, the functional method had more than double the accuracy.

Sheshadri et al. (2020) [12] using load dataset of Karnataka State Demand of September 2019 predicted future loads of October 2019. ARMA, ARIMA, and ARIMAX are proposed for this short-term load forecasting. And for the ARIMAX model, in addition to these two variables other exogenous factors like an hour of the day, day of the week, weekends, public holidays, and weekdays are also considered as inputs. Using Mean Absolute Percentage Error (MAPE), forecasting error for ARMA comes out to be 17.7%, while ARIMA and ARIMAX gave 4% and 3.6% respectively. It may be concluded that ARIMA outperforms ARMA and that the ARIMAX model outperforms the ARIMA model by a little margin because of the addition of exogenous variables.

Citation	Time Frame	Dataset Duration	Techniques used	Evaluation Metrics used
[8]	Short	14 years	SARIMA (BEST), ARIMA	MAPE, MAD, MSD
[9]	Long	5 years	Additive and multiplicative decomposition models (BEST), Additive and multiplicative Holt-Winters models.	MAPE
[10]	Short / Long	3 hours	XGBoost (BEST), ARIMA, SARIMA, RF, LSTM	MPE, MAPE, MAE, RMSE
[11]	Short	8 years	a function-on function linear regression approach (BEST), ARIMA	MAPE
[12]	Short	1 month	ARIMAX (BEST), ARMA, ARIMA	MAPE

Table 1 - Brief review of Statistical methods.

3. LITERATURE REVIEW ON MACHINE LEARNING BASED METHODS

Karunathilake et al. (2017) [13] developed Artificial Neural Networks (ANN) (MLFFN with BPN algorithm) and Multiple Regression (MRA) for short-term load prediction using daily electricity demand from Sri Lanka power system's System Control Center of CEB taking the dataset from 2006 to 2016. It considers various input features like the year, month, day, New Year, Wesak day, P.B.M. Holiday, Development indicator, Poya day, P.B. Holiday, Daily electrical consumption, and Election. This study investigates and analyzes the applicability of ANN in predicting daily power consumption by comparing the performance of ANN with the performance of the MRA model to identify the optimal method with the highest Coefficient of Determination (R2), and lowest Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The ANN model has 74% accuracy, whereas the MRA model has a 38%. Because the Artificial Neural Network model has the lowest RMSE (0.63), MAE (0.02), and greatest R2 (0.738) compared with 0.683, 0.29, and 0.38 respectively of MRA in the findings, it can be inferred that ANN is the best-suited model for forecasting.

Nwulu et al. (2017) [14] proposed a Neural network (Back Propagation Learning Algorithm (BPLA)) and compared it with Linear Regression (LR) for Short-term and mid-term load forecasting. Data set consisting of 768 instances and 8 input attributes taken from the UCI machine learning repository is used to accurately predict the heating and cooling loads with input features like Wall area, Heating Load, Glazing area, Relative Compactness, Surface area, Roof area, Cooling Load, Orientation, Glazing area distribution, and Overall height. Mean absolute error (MAE), Root absolute error (RAE), Root relative squared error (RRSE), Root mean square error (RMSE) are used as performance metrics. Like, for BPLA and LR, RMSE is 2.37 and 3.22 respectively. The BPLA-based artificial neural network models consistently outperform the LR models, for 5-fold and 10-fold validation schemes. The 10-fold cross-validation technique demonstrates the least errors so more accuracy. The sole deviation is the forecast of cooling loads considering conventional validation setup, where the LR model produced smaller errors than the BPLA (neural model).

Aras et al. (2018) [15] proposed two models: residual network (ResNet) and a multilayer perceptron (MLP) for short-term load prediction using data set of 2 years of 22 buildings at a University in Southern California taken at 15-minute intervals. Input features considered are Energy Consumption and hourly Weather features (weather features include outdoor dry-bulb temperature, solar radiation, and relative humidity). The goal of this research is to include deep learning into an energy simulation of metropolitan buildings in order to better estimate their energy usage. Mean Squared Error (MSE) is used as accuracy measurement and error rates are based on ASHRAE Guideline. It is measured 102.26 for baseline (Simulation data, with no machine learning), 59.43 for MLP (64 neurons, 3 hidden layers), and 24.84 for top performer ResNet (2 channels /block, 128 output channels). The results demonstrate that a Deep Residual Network beats all of the evaluated MLP models, with a prediction increase of 74.9% over standard energy modeling methods.

Singla et al. (2019) [16] proposed Artificial Neural Network (ANN) for short term load forecasting by taking load dataset from 66kV substations of PSPCL situated in Bhai Roopa and weather data from the IMD of the first day of January 2015 (24 hours duration). Humidity, Dry bulb temperature, and Dew point are taken as other input features. Error is evaluated using the mean root mean square error (RMSE) and absolute percentage error (MAPE) and comes out to be the order of 0.029 and 0.170 respectively. Based on the observed inaccuracies, it is safe to conclude that the suggested methodology produces somewhat accurate findings and is dependable in estimating the electric load forecast.

Shabbir et al. (2019) [17] performed short-term load prediction by using SVM regression, tree-based regression, and linear regression. An Estonian household load is taken as a dataset calculated for a whole month with a 1-minute frequency using different sensors. Using Root Mean Square Error (RMSE) as an evaluation metric, SVM-based regression produces the best RMSE values (187.73) since it employs more data, resulting in more accurate predictions. Its RMSE is half that of linear regression and 28% less than tree-based regression. It also takes the least amount of time to train the model.

Citation	Time frame	Dataset duration	Techniques used	Evaluation metrics used
[13]	Short	11 years	ANN (BEST), Multiple Regression	RMSE, MAE, R^2
[14]	Short / Mid	NA	ANN - BPLA (BEST), LR	RMSE, MAE, RRSE, RAE
[15]	Short	2 years	ResNet (BEST), MLP	MSE
[16]	Short	1 day	ANN	MAPE, RMSE
[17]	Short	1 month	SVR (BEST), LR, Tree based regression	RMSE

Table 2 - Brief review of Machine Learning methods.

4. LITERATURE REVIEW ON DEEP LEARNING BASED METHODS

Din et al. (2017) [18] proposed Recurrent Deep Neural Network (R-DNN) and Feed forward Deep Neural Network (FF-DNN) for short-term load forecasting. For training, the dataset collected at the end of every hour in a day is taken from ISO New England (ISO-NE) for 6 states in New England considering from 2007 to 2011. Weather, lagged load, data distribution effects, working and non-working days, and time, these input features were analyzed on time and frequency domain. Prediction errors are calculated using MAPE, RMSE, and MAE for four different seasons. For a whole year, considering the time domain, MAPE for FFDNN and RDNN is 1.42 and 1.30 respectively. According to two case studies, the highest mistakes were discovered in the summer season due to higher temperatures and more social activities and predicted errors were lower for the R-DNN model than the FF-DNN model. The results show that the synergistic application of DNN with TF functional analysis will achieve higher accuracy by identifying important factors influencing power consumption behavior and will unquestionably make a significant contribution to the next-generation power system and the recently adopted smart grid.

Shi et al (2017) [19] proposed Pooling-based DRNN and compared it with classical DRNN, RNN, SVR, and ARIMA for short term load forecasting by taking the Smart Metering Electricity Customer Behaviour Trials (CBTs), Ireland as a dataset for the duration of 1st July 2009 to 31st December 2010. Input features were of three types: questionnaires and corresponding answers from surveys, half-hourly sampled electricity consumption (kWh) from each participant, and customer type, tariff, and stimulus description. Mean absolute error (MAE), Normalised root mean squared error (NRMSE), and Root mean squared error (RMSE) were used as performance metrics. In comparison to classical DRNN, the suggested PDRNN reduces RMSE and NRMSE by 6.45% and MAE by 6.96%. When compared to ARIMA, PDRNN reduces RMSE and MAE by 19.46% and 16.28%, respectively. Considering RMSE, the proposed approach beats SVR by 13.1%, ARIMA by 19.5%, and conventional deep RNN by 6.5%. Correlations and interactions between neighboring homes are possible with the suggested load profile pool. Automatically new features can be produced through deep hierarchical levels, increasing the volume and diversity of inputs.

He et al. (2017) [20] proposed Parallel CNN RNN and compared it with CNN RNN, DNN, Linear regression, and SVR for short-term load forecasting. 3 years, hourly load dataset of a city in North China is taken with temperature, day of week, the hour of day, and holiday as other input attributes. Our objective is to forecast hourly loads one day (24 hours) in advance. As evaluation metrics Mean average error (MAE) and Mean absolute percentage error (MAPE) is used. In both MAE and MAPE, the proposed approach outperforms all baselines. When compared to the linear regression method, the testing MAE was reduced by 51.9%, while the MAPE was lowered by 52.2%. Even using the CNN RNN technique, which is rather strong, the solution reduces MAPE and MAE by around a 5% relative decrease. This illustrates the parallel CNN structure's capacity to extract features. SVR gets outperformed by the DNN baseline, demonstrating deep learning's efficacy. Furthermore, the testing MAE and MAPE are 15.587 and 2.110, respectively, when manually extracted features are combined with the DNN baseline. This might imply that deep learning algorithms can extract more accurate feature representations from raw data.

Kim et al. (2018) [21] used the UCI repository dataset of individual household electric power consumption with a one-minute sampling rate from 2006 to 2010 provided long-term load forecasting. 9 Input features including date, voltage, global reactive power, global intensity, time, global active power were taken. The proposed CNN-LSTM hybrid neural network, which can draw out Spatio-temporal information to accurately forecast, are compared with Linear regression (LR), Decision trees (DT), Random Forest (RF), Multilayer perceptron (MLP) using Root mean square error (RMSE) gave median inaccuracies of 0.38, 0.57, 0.62, 0.58 and 0.76 respectively. Using the convolution and pooling layer, the suggested CNN-LSTM technique decreased the spectrum of time series data. Learning loss graphs were utilized to validate the efficacy of the suggested technique, and the CNN-LSTM hybrid model demonstrated stable learning when compared to the conventional LSTM method. CNN-LSTM technique is utilized to automatically extract correlations and temporal information from multivariate time series data.

Citation	Time frame	Dataset duration	Techniques used	Evaluation metrics used
[18]	Short	5 years	R-DNN (BEST), FF-DNN	RMSE, MAE, MAPE
[19]	Short	1.5 years	Pooling-based DRNN (BEST), SVR, ARIMA, RNN, DRNN	RMSE, NRMSE, MAE
[20]	Short	3 years	Parallel CNN RNN (BEST), Linear Reg, SVR, DNN, CNN RNN	MAPE, MAE
[21]	Long	5 years	CNN-LSTM hybrid neural network (BEST), LR, DT, RF, MLP	RMSE

Table 3 - Brief review of Deep Learning methods.

5. METHODS: PROS AND CONS

The pros and cons of all the methods under the three categories namely Statistical, Machine Learning, and Deep learning are discussed here in this Table 4.

METHODS	PROS	CONS
ARIMA	Ignoring the remaining non-linear data, it extracts and approximates the linear components of the original time series; To generalise the forecast, just past data from a time series is required; reliable forecasting.	The underlying theoretical model and structural linkages are less clear than in certain basic forecasting models, such as simple exponential smoothing and Holt-Winters. Long term and series with turning points are difficult to forecast.
SARIMA	Strong underlying theory; Reliable assessment of changing trends over seasonal and time patterns; parameters are relatively few.	Seasonal index is not clear; explaining "how the model works" is difficult and also analyzing coefficients; if not properly used there is risk of misidentification and overfitting.
ANN	Are adaptable; good for modelling nonlinear data with a high number of inputs; quick predictions when trained; and perform best with more data points.	No way of knowing how much each independent variable affects dependent variables (black boxes); Training with conventional CPUs is quite computationally expensive and time consuming; heavily reliant on training data,

		makes it prone to overfitting and generalisation problems; Input with a fixed length.
REGRESSION	Implementation is easy and straightforward; useful for examining the relationships between the input variables.	Is sensitive to outliers, and lacks practicality because most issues in real world aren't linear.
SUPPORT VECTOR REGRESSION (SVR)	It is very flexible; performs well on non-linear situations; and is not influenced by outliers.	It is necessary to apply feature scaling; not wellknown and difficult to comprehend.
RANDOM FOREST (RF) REGRESSION	Strong, accurate, and capable of handling a broad range of problems, including non-linear ones.	Overfitting is readily possible; we need to select the number of trees; and there is no interpretability.
FUZZY LOGIC	Basic structure, readily built; resilient system since no exact inputs are necessary; can be programmed using minimal data, so it does not take up a lot of memory space; adaptable, and the rules may be changed.	Because the system works with inaccurate data and inputs, accuracy is compromised (less stable); no single systematic way to solve a problem; are completely reliant on human knowledge and expertise; require extensive testing for validation and verification.
CNN	CNNs are parallelizable, but RNNs are not; their ability to use max-pooling layers to extract the most critical characteristics (key information); Prediction outcomes with high accuracy; more powerful than ANN and RNN.	Input with fixed length; problem with Vanishing and Exploding Gradient; Inability to be spatially invariant while dealing with input data; require large amount of training data.
RNN	Designed to recollect each snippet of data all through time (useful in time series prediction); Can deal with inputs of any length; Larger input sizes do not increase the size of the model; may handle any length of inputs using their internal memory, which isn't the situation with feedforward neural networks.; across time steps, weights can be shared.	Computation is slow due to its recurring nature; Training can be challenging, especially when employing relu or tanh as activation functions to handle lengthy sequences; exploding and gradient vanishing problems; compared to CNN, it has fewer feature compatibility.
LSTM	Long-term sequence dependencies can be modelled; Since the internal memory specification is modified, they are more resistant to the problem of short memory than 'Vanilla' RNNs; no need for fine adjustments because it includes a wide range of parameters including learning rates and input and output biases, complexity of updating each weight is minimised.	With the addition of additional parameters to learn, the computing complexity of RNNs increases (training needs more time); Short-term forecasting is less feasible; Memory requirements are larger than for 'Vanilla' RNNs owing to the inclusion of many memory cells.
HYBRID	In order to capture many types of relationship in time series data, researchers combined the advantages of linear and nonlinear models; Generally have high processing speed; and are simple to implement; model's performance is enhanced.	Some have sophisticated architecture, while others don't., depends model to model.

Table 4 - Pros and Cons of forecasting models discussed in this paper.

6. CONCLUSION

Electricity demand is rising at an exponential rate as the number of electronic equipment grows. Various forecasting models have been proposed during the previous decade. This study looked at new research in the field of electric power consumption prediction, which is one of the fields of smart grid data analysis. Statistical approaches and machine learning are two well-known techniques for forecasting electricity. Deep learning is viewed as the most encouraging methodology because of its adequacy in an assortment of fields, including computer vision, image processing, and medicine. This document gives a concise outline of the different methodologies utilized for electrical load forecasting.

The study is subdivided based on the problems discussed, potential methods used as solutions, type of forecasting, dataset, its duration with different input features, and results measured with various performance metrics. Tables are used to display a brief of paper and the pros and cons of methods used. This paper contains sufficient information, insights, and references on load predictions. The outcomes of various sorts of forecasts vary. For determining optimal regulation of power systems, short term forecasts are useful, while for planning and financing the power sector mid-to-long-term forecasts are suitable.

A series of procedures are taken to make the forecast. Data is first gathered, cleansed, and chosen, and then a prediction algorithm is applied to the dataset. In the literature, the algorithms employed in the forecasting step are classified as statistical, machine learning, and deep learning approaches. In the last stage, the algorithm's performance is assessed using performance metrics.

All of the researchers want to make sure that the model they create can properly predict power consumption. However, differences in data set size and input feature types make it difficult to determine which evaluation measure and Machine Learning algorithm works best.

In the conclusion, future research includes: to increase the training dataset size, using more relevant input features, utilizing the best pooling technique by grouping consumers with comparable characteristics, such as similar geographic areas and social standing, using more than one or advanced type of algorithms for comparison, move towards hybrid techniques (as are efficient, flexible and have better computational complexity), etc.

We believe that this work will aid the scientific community, researchers, and practitioners in future development and provide a contribution to this new demanding and essential field.

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