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Predicting Household Electric Power Consumption Using Multi-step Time Series with Convolutional LSTM

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ABSTRACT

Energy consumption prediction has become an integral part of a smart and sustainable environment. With future demand forecasts, energy production and distribution can be optimized to meet the needs of the growing population. However, forecasting the demand of individual households is a challenging task due to the diversity of energy consumption patterns. Recently, it has become popular with artificial intelligence-based smart energy-saving designs, smart grid planning and social Internet of Things (IoT) based smart homes. Despite existing approaches for energy demand forecast, predominantly, such systems are based on one-step forecasting and have a short forecasting period. For resolving this issue and obtain high prediction accuracy, this study follows the prediction of household appliances' power in two phases. In the first phase, a long short-term memory (LSTM) based model is used to predict total generative active power for the coming 500 hours. The second phase employs a hybrid deep learning model that combines convolutional characteristics of neural network with LSTM for household electrical energy consumption forecasting of the week ahead utilizing Social IoT-based smart meter readings. Experimental results reveal that the proposed convolutional LSTM (ConvLSTM) architecture outperforms other models with the lowest root mean square error value of 367 kilowatts for weekly household power consumption.

1. Introduction

In recent years, the topic of social Internet of things (IoT) has become an emerging IoT field of great interest. IoT is now an established paradigm that supports a variety of applications and services [19]. Social IoT is based on introducing a new vision of cooperation between smart objects in a similar way to what happens for humans when they communicate to achieve a common goal. So, several interconnected IoT devices can relate to each other and provide smart services in different contexts. The sectors that can benefit from this new paradigm and the connection of different smart objects to obtain increasingly pervasive and effective answers to their problems are those of transport, water, energy, etc. The potential of energy efficiency management and consumption forecasting has gradually been recognized by governments and energy research institutes as an important part of sustainable development. With the increase in population and living standards of citizens, household energy consumption is increasing steadily [63]. Power generation and distribution systems keep trying to maintain a balance between electricity demand and supply. According to the report of the annual energy outlook 2020, the annual growth of electricity demand averages about 1% over the 2019–2050 period [11]. A 90% of the time is spent indoors indicating the energy requirements of the buildings [48]. As a result, 80% to 90% of the buildings' life cycle is spent on people's occupational activities and comfort [59]. Consequently, the building sector consumes the most significant portion, i.e., 39% of the total energy consumption globally [40], and has 38% greenhouse gas emissions [49]. Electricity cannot be stored due to its physical characteristics, it must be consumed as it is generated in the plant [26]. With the continuous increase in the population and increased demand for energy,

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power consumption forecasting systems have become increasingly important recently.

Fluctuation of electric power consumption mainly depends upon the number of household electric items and the behavior of residents. Household electric consumption is derived from household occupancy. To implement household energy disaggregation based on occupancy aiming at automatic energy reduction is studied by utilizing IR ultra-wideband (UWB) radar and electrical signals [10]. Authors estimated the household occupancy using smart meter power consumption dataset [6]. They suggested an expandable and personalized energy efficiency method and also gave a new idea for the implementation of Social IoT-based smart metering infrastructure. However, consumer privacy concern is the most challenging issue for policymakers in smart metering implementation.

The performance of machine learning (ML) models mainly depends upon the data representation. While deep learning (DL) deals with the nonlinear transformation that provides high-level abstraction and eventually more profit [8]. DL techniques have been extensively used in various applications [44] and convolutional neural networks (CNN) surpass other existing methods in image classification [54] by preserving relationships between pixels. A recurrent neural network (RNN) is superior in natural language processing (NLP) tasks by storing sequential information. RNN also ensures that time-series information can be retained [17]. Long short-term memory (LSTM), a variant of RNN, is being used to extract spatial and temporal features in combination with CNN. The electrical energy consumption prediction problem is a time series problem. Kim et al. predicted energy consumption by combining CNN with LSTM [31]. They achieved higher performance than existing approaches by using a hybrid deep learning model. They also analyzed the variables influencing the prediction of power consumption. However, it is difficult for the traditional deep learning approaches to model spatial and temporal features of energy consumption.

Forecasting of electric energy consumption is a multivariate time series problem that predicts power consumption. However, these irregular seasonal trends of power consumption make it difficult for prediction methods to predict electric energy consumption [1]. Dataset provided by the UCI repository consists of seven variables and power consumption sampling for 2007–2011 and is considered a benchmark dataset in time series forecasting. These time series were collected from various Social IoT devices such as smart meter readings and used, in this study, as input for convolutional LSTM (ConvLSTM), a hybrid deep learning model that combines characteristics of CNN with LSTM. So, ConvLSTM architecture is used for electrical energy consumption prediction, where ConvLSTM-two dimensional (ConvLSTM-2D) finds a correlation of multivariate variables and LSTM layers build time series based temporal information to generate the final prediction. LSTM layer output is fed to the fully connected layer that finally predicts power demand. In this work, multi step-time series power consumption problem is explored that is to estimate the expected electric power consumption for the next week by using recent consumption. Then forecast the total active power of each day to the next week by the predictive model. This work aims at helping the planning expenditure and fulfilling the electricity demands of a single household on the supply side. The main contributions of this study are:

- A hybrid deep learning framework is designed which combines CNN and LSTM models to predict the weekly power consumption for single households. It is built to predict total generative active power for the coming 500 hours.
- Contrary to existing approaches that are single-tier, this study follows a two-phase approach of predicting generative active power in the first phase using LSTM and energy consumption prediction in the second phase using proposed ConvLSTM.
- Multi-step forecasting is used to facilitate application usage in the real world, such as social IoT-based smart grid planning. To prove the significance of the proposed model, extensive experiments are performed on the power consumption of a single household dataset.

The rest of the paper is organized as follows. Section 2 discusses a few pieces of research related to the current study. Section 3 presents an overview of the methodology adopted for the current research as well as a detailed description of the tweet dataset used for the experiment. Results are presented in Section 4. Section 5 describes other possible Social IoT applications of the sensors used when they are integrated into a larger Social IoT architecture. Finally, Section 6 discusses conclusion and future work.

2. Related work

The selection of the time series forecasting method depends upon many factors, like the availability of relevant datasets, desired accuracy, and so forth. Conventional statistical-based approaches have been used by many researchers to solve time series problems. With the immense progress in ML and artificial intelligence, researchers are now utilizing deep learning models to forecast electric load problems in Social IoT platforms. In recent years, Social IoT has become a hot topic, of great interest in various contexts. Business, smart homes, and utilities are just some of the sectors that are benefiting from research in this emerging field. The interconnectivity of these smart devices, and the possibility of a continuous sharing of information between them, also lead to problems such as reliability and data protection which are however significant challenges for this new paradigm [47].

Statistical models, based on mathematical models, deal with the load as an input factor. These methods have been used for many years to forecast electric power consumption and include curve fitting and smoothing techniques. Different methods used to deal with time series problem for load forecasting include, Autoregressive moving average (ARMA) model [24], seasonal ARIMA model [13], ARIMA model [35] [18], adoptive load forecasting [56], Kalman filtering [50] and multiple regression [41]. The major shortcoming of these approaches was to deal with forecasting as a linear problem. Electric consumption forecasting is a multivariate, multidimensional, and complex problem, these statistical methods were not able to extract nonlinear relationships between independent variables.

On the other hand, advanced ML approaches are performing well to explore patterns and regularities of data and utilize them effectively to forecast time series problems. To forecast electric power consumption, most commonly used ML models include support vector regression [14], random forest regression [9] and deep neural network [46]. The authors of [39] applied DL models to estimate electric energy consumption at the residential building level with different time resolutions. The authors applied state-of-the-art models named Factored-Conditional Restricted-Boltzmann Machine (FCRBM) and Conditional-Restricted Boltzmann-Machine (CRBM) to explore variables causing fluctuation in energy consumption. In their experiment, FCRBM outperformed the other deep learning modes.

In [51] authors presented a shape-based approach to predict power load curve clustering for households as well as prediction and estimated usage time of devices. Based on the current day load curve, they predicted the next day's prototype. The authors also estimated the use of electric devices during specific hours. In [65] authors suggested efficient use of households by analyzing consumption behavior. They provided a deep understanding of the user's behavior pattern in energy consumption to develop efficient strategies for the future. Researchers [36] combined stacked auto encoders with ELM technique to reduce training time and to improve performance for load forecasting. Results proved that their proposed approach performed well in energy consumption prediction. However, the dataset used in their experiment does not contain much data but the proposed model still extracted useful information and performed well.

Hybrid models have been employed by many researchers to overcome individual models' limitations. A similar approach is discussed in [60] to forecast residential power consumption by combining CNN with LSTM. Furthermore, the authors proposed a k-step forecasting method to solve small steps for more response time. They also extended their work to deal with prolonged response time by exploring different intervals of time. In [31] authors also utilized CNN-LSTM to predict electric power consumption. They also explored important variables having a high impact on model results. In the end, the authors also compared experimental results with ML models to prove the efficiency of the proposed approach. The study [42] employs a hybrid model for electricity consumption prediction for Slovakia. Initially, the performance of the transverse set of Grey models is analyzed, as well as nonlinear Grey Bernoulli models are adopted. Furthermore, a hybrid model is designed that combines Grey models with a feed-forward backward propagation network for hourly electricity consumption prediction. The proposed hybrid model tends to show the best accuracy for prediction.

The authors adopt a modified K-Means clustering algorithm to predict energy consumption in [5]. The algorithm is adopted to divide the users into different groups which are automatically decided based on the energy consumption patterns. The authors discuss the findings concerning seven clusters of users and make recommendations accordingly. Authors [25] applied three deep learning models to predict household energy consumption that are vanilla LSTM, the sequence with attention mechanism, and sequence to sequence. In their experiment vanilla LSTM performed best to predict energy consumption patterns with the root mean square error metric. These models were not able to predict trends at a specific time. In [34] authors proposed an intelligent framework for the smart buildings to forecast multiple electric energy of two smart buildings using transfer learning. The authors applied k-Mean clustering and made clusters of daily load and also found the optimal number of clusters. Then they performed electric consumption forecast and compared different approaches in terms of performance and computational time.

Energy consumption prediction problems of individual customers of residential areas are analyzed in [3]. In the first step, the authors applied clustering to find the regularity of power consumption. Secondly, they used a hybrid DL model, CNN-LSTM to forecast household power consumption for single steps as well as multi-step. Clustering-based approach is utilized in [52] to predict electric power. Their proposed model consists of a deep auto encoder and clustering algorithm SOM. The authors provided a timeline as well as energy usage behavior on daily basis, weekly basis, monthly basis, and yearly basis. Authors of [32] proposed a framework to forecast day household electric power consumption on an individual level. Authors considered contextual data of calendar, weather, and load history of households. They also explored significant time-series features. Their model's performance is effective only on the dataset with similar economic status and similar weather conditions.

The relationship of electric energy consumption with the temperature of occupancy space of buildings was explored by [7]. They minimized electric energy wastage and provided a cost-effective solution. Filter iterative optimization ensemble strategy was proposed by [38] in an improved way. The authors combined the ranking method and iterative optimization method to improve the performance. It is observed that by selecting suitable kappa coefficients, excellent performance can be achieved. Authors in [16] proposed a neuroevolution method and explored optimal parameters to forecast on time series dataset. The proposed approach performed well for a short-term electric energy forecast.

The aforementioned analysis of time series-based energy consumption problems shows that there have been a lot of efforts in this area. In Table 1, we present a summary of the above research works, emphasizing both the achievements and the limitations. There is a challenging research tendency related to many factors such as behavior toward the use of household energy consumption. The motivation behind this work is to explore power usage patterns and their relationship with time of use and days of week etc. Deep insight exploration of all factors to model irregular patterns will increase understanding and will provide better solutions for household energy usage by using the Social IoT infrastructure of smart meters.

3. Proposed methodology

The proposed hybrid neural network model is based on CNN and LSTM layers. Fig. 1 depicts the suggested architecture and the two phases implemented for predicting global active power and weekly residential energy consumption. Phase I uses an LSTM-based model to forecast the upcoming 500 hours of global active power. While in phase II, the ConvLSTM model predicts weekly electricity usage using time series data collected from Social IoT smart meter readings. ConvLSTM-2D layer captures spatial characteristics by convolution operations using a sliding window [30]. After reducing noise, these features are transmitted to the LSTM layer, which models irregular time-based information. The suggested model can then predict energy consumption using time series data in a connected hierarchy. The ConvLSTM-generated results are then evaluated using the root mean squared error measure.

3.1. *Convolutional neural network (CNN)*

Convolutional Neural Networks (CNNs) have remarkable feature extraction capabilities, which allow them to have important applications in image classification, recognition, and many other fields [37]. CNN is most frequently used DL model which is being extensively used in classification tasks related to computer vision [4,53,43]; however, applied to several other domains like client collaboration in cloud [58], disease prediction [55], arrhythmia detection [20] and forgery analysis [45]. CNN extracts important features from raw data efficiently by convolution and pooling layers. CNN is a feed-forward deep learning model and it is an extended form of a multi-layer neural network, but it contains parameter sharing and sparse interaction property [29]. The conventional multi-layered deep neural network model works as a fully connected network (each input neuron is connected with each output neuron) between an input layer and output layer. For instance, for m number of inputs and n number of outputs, resultant weight matrix entries will be $m \times n$. In CNN size of the weight matrix is reduced to $k \times n$ by applying kernel $k \times k$. After the training phase, there is a single matrix of $k \times n$ size for learning. The training ability of CNN can be improved by parameter optimization and by making it a deeper network.

1-D convolutional layers are used to deal temporal convolutional process, which is appropriate for univariate time series data processing. In temporal CNN $k \times 1$ kernel is used instead of $k \times k$ kernel. If input function is $g(x)\epsilon[l, 1] \rightarrow R$, then kernel is $f(x)\epsilon[k, 1] \rightarrow R$. Mapping of input and kernel is presented as under.

Table 1
Summary of discussed research works on electric power consumption.

Ref.	Year	Method	Dataset	Results	Limitations
Machine Learning Approaches					
[39]	2016	Factored-Conditional-Restricted Boltzmann-Machine (FCRBM), Conditional-Restricted-Boltzmann-Machine (CRBM)	Electric power consumption of individual household dataset	FCRBM outperformed other techniques to solve time series power consumption problem.	Validation is not performed. Single dataset is used.
[51]	2017	Shape-Based Approach Dynamic-Time-Warping (DTW)	Load curves (23,254) of households (1057) prepared by Opower Corporation.	Predict behavior of user on power consumption of household. 50% reduction in representative groups.	A smaller dataset is used.
[36]	2017	Stacked Auto-encoder (SAE) & Extreme Learning Machine (ELM)	Applied building consumption data.	Combined SAE and ELM to predict energy consumption of specific building.	Validation is not performed. The knowledge of periodicity is not incorporated.
[16]	2020	Genetic algorithm	Global electricity consumption dataset registered in Spain, Jan. 2007–June 2016.	Predicted short term energy consumption demand.	No validation. The package used for the model does not allow parameter optimization.
[5]	2021	K-Means clustering	Energy consumption prediction related to different user groups.	Broadband network energy consumption data. Analysis of 7 groups with different energy consumption patterns.	High computational complexity.
Deep Learning Approaches					
[60]	2018	CNN-LSTM	Electric energy consumption data collected from five London households.	Applied hybrid deep learning and also introduced k-step forecasting technique.	The model is not suitable for short-term prediction.
[31]	2019	CNN-LSTM	Electric power consumption of individual household dataset.	Forecast residential power consumption and also analysis of important variables.	A smaller dataset size. High computational complexity of the model.
[25]	2020	Vanilla LSTM, the sequence with attention mechanism sequence to sequence	Individual household power consumption dataset, Dec. 2006–Nov. 2010	Predicted energy consumption in the residential building by applying three deep learning models.	Simple deep learning models with lower prediction accuracy.
[34]	2020	Transfer Learning, LSTM, (TLL) & MEC-TLL	Smart building dataset located in Korea, Jan. 2016–Dec. 2018	Multiple electric energy forecasting using transfer learning.	It can not handle real-time energy consumption prediction.
[3]	2020	CNN-LSTM	Data gathered during smart grid smart city (SGSC) project initiated by Australian govt.	Multiple electric energy forecasting using transfer learning.	Performance is reduced with irregular usage behavior.
[52]	2020	Deep Auto-encoder, SOM clustering algorithm	Monthly energy consumption of Gainesville, USA 2006–2010 Single house electric consumption dataset, Dec. 2006–Nov. 2010.	Cluster based electric energy consumption prediction using smart sensors.	High computational complexity due to clustering process.
[32]	2020	Deep residual neural network	Pecan street dataset 2015–2018.	Short term load forecasting using deep learning.	Model re-training is needed for new data.
[7]	2020	Elman RNN & exponential model	Real-time based weather-station placed on roof of Clemson University.	Predicted electrical power consumption using power loads in future.	Unable to handle real-time energy consumption prediction.
[38]	2020	Ensemble learner	Electric energy consumption info of a city presented by SGCC, Jan. 2018–Feb. 2019.	Combined iterative optimization & ranking method for power consumption prediction.	High computational complexity due to iterative learning process.
[42]	2022	Grey nonlinear models, hybrid model	Electricity maximum prediction for Slovakia.	Hybrid model shows better performance with the data obtained from official system of Slovakia.	External factors for data analysis are not considered.

$$h(y) = \Sigma_{x=1}^{k} f(x) \cdot g(y \cdot d - x + k - d + 1) \qquad (1)$$

After the temporal operation, the dimensions of the dataset were increased to m. Thus, Conv 1-D is applied to time series data, and the univariate dataset is examined for multidimensional characteristics that serve as input for the LSTM layer.

3.1.1. *Long short term memory (LSTM)*

LSTM is an extended form of RNN which has a feedback connection [62]. It does not only consider a single data point but also considers the entire data sequence, therefore it is appropriate for time series data processing and classification. RNN faces a vanishing gradient problem while dealing with a long series of data samples [27], which is also a reason for the introduction of the LSTM model [23]. The cell memory unit is a part of LSTM which has the ability to forget previous memory and to add a new part of information. LSTM model consists of four components: input gate, forget gate, output gate, and cell state. These all 3 gates control information flow within the cell and the cell state saves values at arbitrary intervals of time. The process sequence is presented in equations.

$$f_t = sigmoid(W_f x_t + U_f h_{t-1} + b_f) \qquad (2)$$

$$i_t = sigmoid(W_i x_t + U_i h_{t-1} + b_i) \qquad (3)$$

$$\tilde{c_t} = tanh(W_c x_t + U_c h_{t-1} + b_c) \qquad (4)$$

$$c_t = i_t \odot \tilde{c_t} + f_t \odot c_{t-1} \qquad (5)$$

$$o_t = sigmoid(W_o x_t + U_o h_{t-1} + b_o) \qquad (6)$$

$$h_t = o_t \odot tanh(c_t) \qquad (7)$$

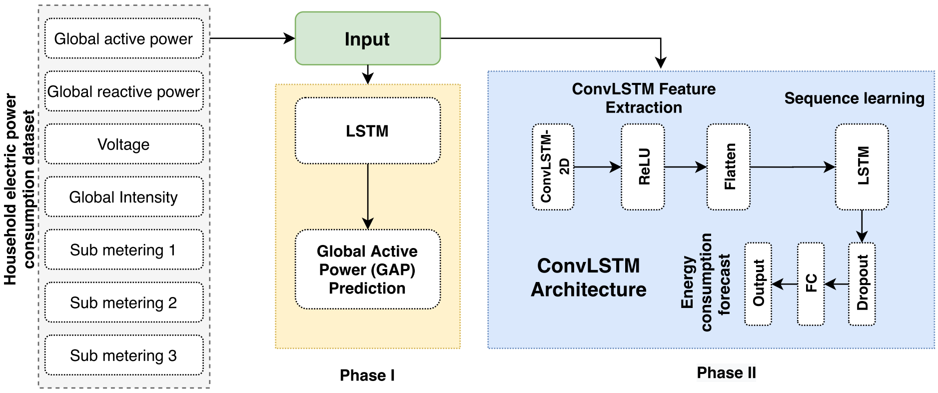

Fig. 1. Architecture of the proposed framework. Two phases work independently where the first phase predicts the global active power consumption for the next 500 hours using the LSTM model only. While phase 2 uses the time series data for weekly power consumption forecasting using the data collected through Social IoT-based smart meters.

Table 2
Layers structure of the CNN-LSTM model.

Layer	Parameters
Conv-1D	Filters=64, activation='RelU', kernel_size=3
Conv-1D	Filters=64, activation='RelU', kernel_size=3
MaxPooling1D	pool_size=2
LSTM	Units=200, Activation='RelU', Return_Sequences=True
Dense	Units=100, activation='RelU'
Output	loss='RMSE', Optimizer='Adam'

Table 3
Layers structure of the CNN-LSTM model.

Layer	Parameters
ConvLSTM-2D	Filters=64, activation='RelU', kernel_size=(1,3), n_steps=2, n_length=7
LSTM	Units=200, Activation='RelU', Return_Sequences=True
Dense	Units=100, activation='RelU'
Output	loss='RMSE', Optimizer='Adam'

where x_t is the input vector for the t-th time, $\tilde{c_t}$ is the vector of cell input activations c_t is the cell status at time t, c_{t-1} is the cell status at time $t-1$ i.e. previous or last time frame. The symbol f_t represents forget gate, i_t represents input gate and o_t represents output gate. Along with suitable parameter tuning, the output value h_t is computed on the basis of c_{t-1} and $\tilde{c_t}$ values. Weights: W_i, W_f, W_o, W_c, are calculated on the basis of difference between the actual value and output value. The weights U_i, U_f, U_o, U_c are obtained on the basis of the connections with the hidden layers and, finally, b_i, b_f, b_o, b_c are bias parameters.

3.2. CNN-LSTM

CNN-LSTM design can be varied according to the adjustments of parameters of the network layers. It mainly consists of a convolutional layer, LSTM layer, pooling, and dense layers [64]. The size of filters, kernel, and stride can be adjusted at each layer, and this adjustment affects performance and learning speed [21]. As the number of parameters increases or decreases, performance changes. Parameter tuning to build an optimal framework depends upon input data. Electric power consumption is a time-series issue; temporal information is maintained by setting the kernel size to 3. A total of seven input variables are passed through the convolution layer. The output of the convolution layer is transmitted to the pooling layer, and then to the LSTM layer. Tuning values for parameters are shown in Table 2.

3.3. ConvLSTM

Convolutional Long Short Term Memory (ConvLSTM) is an extension of LSTM which contains convolutional operation in the cell of LSTM. It is a special form of RNN, which is also effective in learning long-term dependency. In ConvLSTM, matrix multiplication at each gate of the cell is replaced with the convolution operation. This step helps in capturing spatial features in multidimensional data by convolution which makes this approach more advantageous over the existing CNN-LSTM model. ConvLSTM has been used to solve many problems like travel demand prediction [57], detection of slip direction [61] and agricultural forecasting [2].

The combination of convolution and LSTM is used to preserve spatial information temporally when data is collected over successive time intervals to forecast electric energy consumption. Seven input layer attributes are passed to the ConvLSTM layer, which is then followed by the decoding flatten layer. The output of the ConvLSTM is then supplied to the LSTM layer, which is followed by layers that are fully connected. The performance of the models is optimized by fine-tuning several hyperparameters using the grid search method [15]. A complete list of adopted hyperparameters is provided in Table 3.

4. Experimental results and discussions

In this section, the electric power consumption dataset used in the experiment, experimental setup, and results of both phases of the proposed approach are discussed. In phase I, global active power consumption is predicted using LSTM. In phase II, single household power consumption is forecasted for a week by leveraging the information made available by Social IoT smart devices. To achieve the goal of energy prediction for the week ahead, experiments are performed in five scenarios: (i) LSTM model with univariate input and vector output (ii) Encoder-Decoder LSTM model with Univariate Input (iii) Encoder-Decoder LSTM model with Multivariate input (iv) CNN-LSTM Encoder-Decoder model with Univariate input (v) ConvLSTM Encoder-Decoder Model with univariate input.

4.1. Electric power consumption of household dataset

This study utilizes the electric power consumption of the household dataset that is provided by a machine learning repository, UCI [22]. Dataset consists of a sampling rate of power consumption in one minute over the period from 2007 to 2011. Table 4 presents the seven variables of the electric power consumption dataset with three variables provided by energy consumption

Table 4
Household consumption dataset features.

Attribute	Description
Global active power	Household global minute-averaged active power (in kilowatt)
Global reactive power	Household global minute-averaged reactive power (in kilowatt)
Voltage	Minute-averaged voltage (in volt)
Global intensity	Household global minute-averaged current intensity (in ampere)
Sub metering 1	It corresponds to the kitchen, where there is an oven, a dishwasher and a microwave, hot plates being not electric but gas powered (in watt-hour of active energy)
Sub metering 2	It is at a laundry room, which contains a tumble-drier, a washing machine, a refrigerator and also a light (in watt-hour of active energy)
Sub metering 3	It refers to an electric water heater and an air conditioner (in watt-hour of active energy)

sensors. As raw data contain a number of missing values and an inappropriate recorded time frame, so it is not suitable for good prediction accuracy. Missing values are filled by taking the mean from the relevant column of the dataset.

4.2. Experimental setup

Table 2 presents the hybrid DL model settings utilized in the experiment. Hyperparameters are tuned to achieve good results for the proposed model (ConvLSTM) based on CNN & LSTM. Keras library is used to adjust hyper parameters for each model, and each hyper parameter was selected empirically. The forecast consists of seven values containing one value for each day in a week. Units of power are kilowatts. Both MAE and RMSE can be used in multi-step forecasting problems. RMSE is more punishing in forecasting errors, by giving errors large absolute values, so we used RMSE as an evaluation parameter [12]. Equation (8) is used to compute the RMSE value. If y_i is a vector of n predictions built from n datapoints sample on all variables of electric power consumption, and y is the observed power consumption vector of the variable to be predicted.

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n}(y - yi)^2}{n}} \tag{8}$$

4.3. Global active power prediction

In phase I of the proposed model, LSTM predicts global active power consumption on the household electric power consumption dataset successfully. It can be seen in the Fig. 2 that excellent performance is achieved in the prediction of global active power prediction. Predictive results are quite similar to the actual values/ground truth. The x-axis shows the time step which indicates the hours for which the prediction is made. Fig. 3 depicts the loss curve and demonstrates that LSTM works well in predicting active power consumption. Active power consumption is predicted by LSTM with an RMSE of 0.617%.

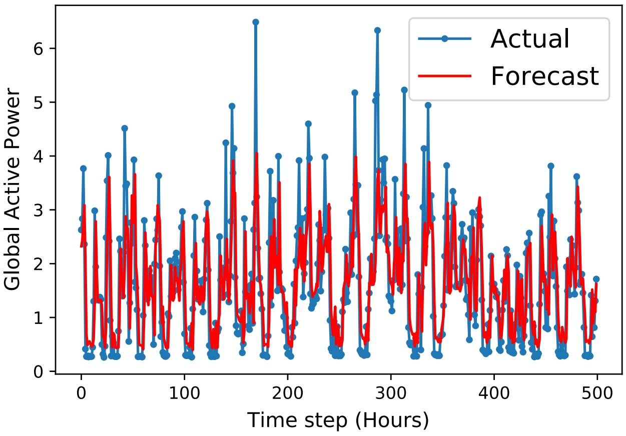

Fig. 2. Prediction results of global active power consumption data.

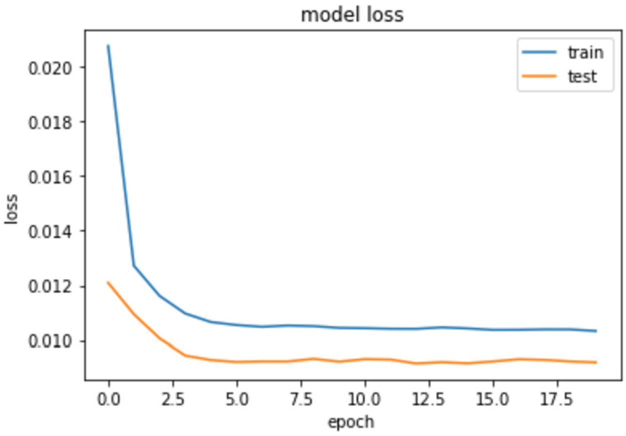

Fig. 3. Loss curve of model predicting active power consumption data.

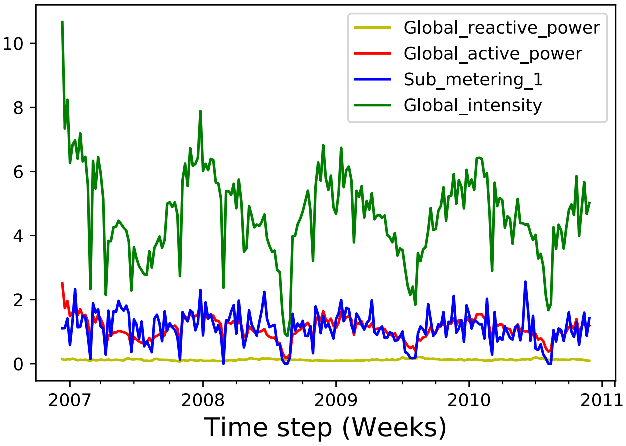

Fig. 4. Features re-sampled over a week.

4.4. Weekly prediction for household power consumption

Traditional forecasting of power consumption focuses on one-step forecasting solutions [33,46]. In this study, we design a forecasting strategy for electric power consumption uniformly. We performed different experiments in four scenarios. Time step data from the dataset is long enough and requires a reorganization step. Household power consumption data collected from the repository has time steps in minutes. To reduce sparsity the original dataset is reorganized minutes data per day. Fig. 5 displays the various characteristics of the daily resampled household power consumption dataset. Then it is reorganized to the standard weeks that start on Sunday and end on Saturday. Re-sampling of features over a week is presented in Fig. 4 which indicates the features for global reactive power, global active power, and powers for submeters 1, 2, and 3. By categorizing data in this manner, it will be feasible to estimate next coming week's electricity consumption. In this ex-

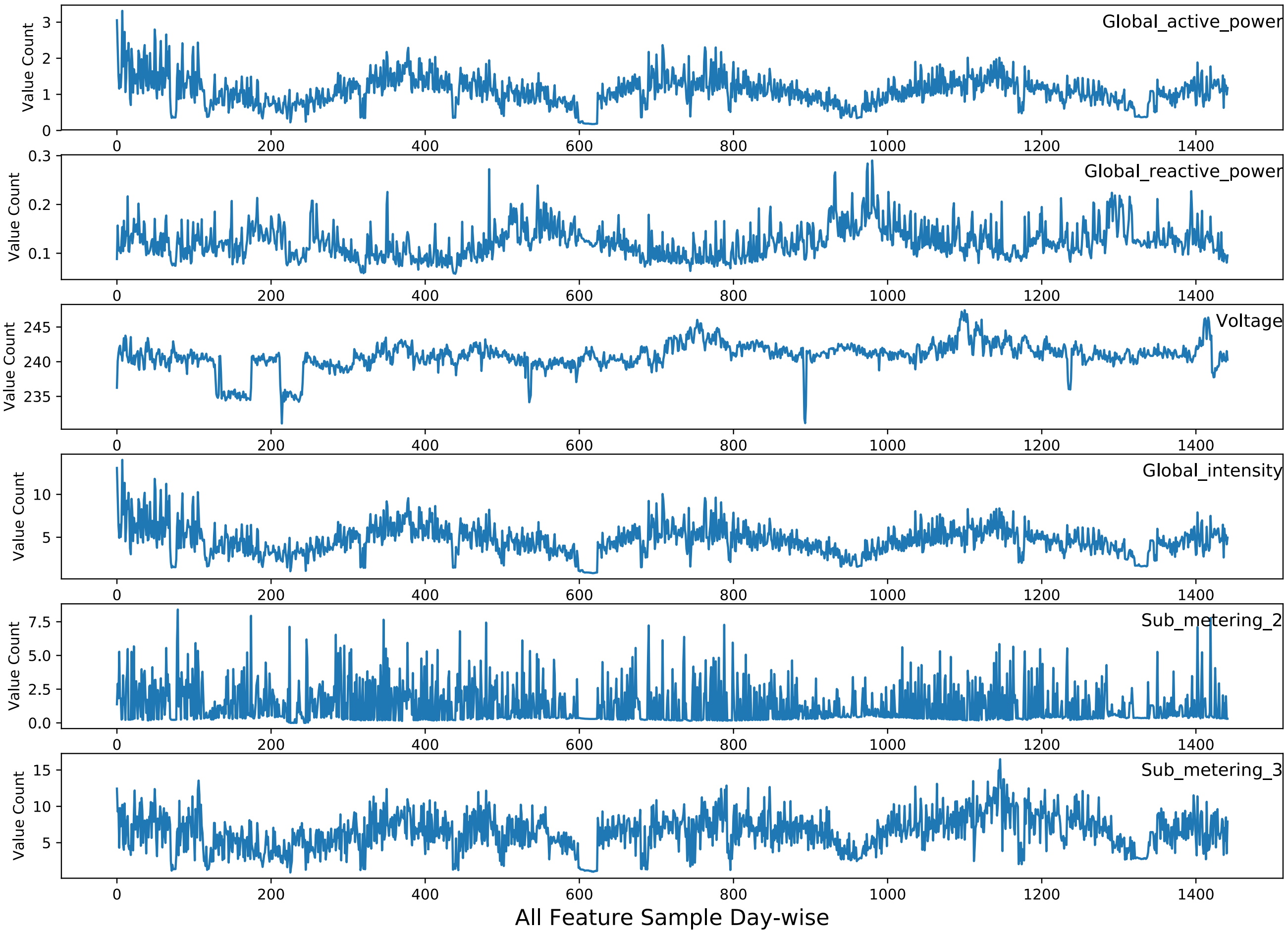

Fig. 5. Features re-sampled over day.

periment, 159 weeks of data are used for model training, whereas 46 weeks of data are used for model evaluation.

4.4.1. LSTM models with univariate input and vector output

LSTM model is used to train on a weekly sequence of daily power consumption and predicts the electric power consumption output vector of the week ahead. LSTM layer with 200 units is followed by fully connected layers with 100 units and an output layer. MSE is used as a loss function and Adam optimizer. We used batch size 16 and trained the model on 70 epochs. In this experiment, *n*_input value used is 7 and retrieved seven days of the output vector. Fig. 6 depicts the seven-day RMSE for univariate input and output vectors. Fig. 6 demonstrates that it is easier to predict energy consumption on weekdays in the middle of the week, while Saturday is the most difficult day to forecast energy consumption.

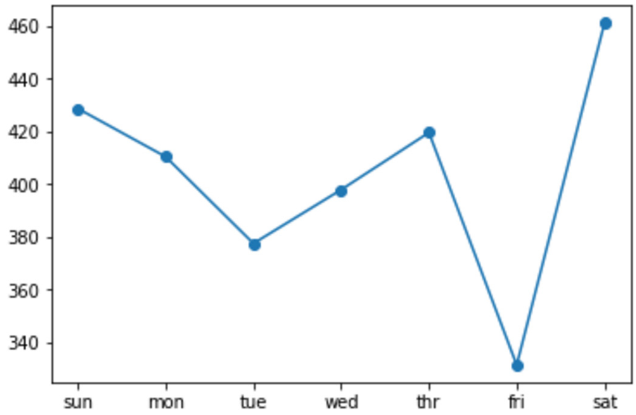

Fig. 6. Line plot of RMSE per day for univariate LSTM with vector output.

4.4.2. Encode-decoder LSTM model with univariate input

In encoder-decoder LSTM model univariate input, where encoder reads the input and decoder generate output sequence. LSTM is defined as a decoder layer with 200 units, then a fully connected layer, and then an output layer. Fig. 7 depicts a line plot of RMSE per day for the encoder-decoder LSTM model with univariate input, which displays a similar error pattern to the LSTM model with univariate input and vector output.

4.4.3. Encode-decoder LSTM model with multivariate input

In this scenario, multivariate input (each of eight variables) is utilized to predict next week for household power consumption. Multivariate input helps in the case where output depends upon times steps from different multiple features not just on the forecasted feature. In this work, the power consumption scenario is explored by using features from previous time steps. Fig. 8 shows that model is more skillful with 376 kilowatts RMSE score.

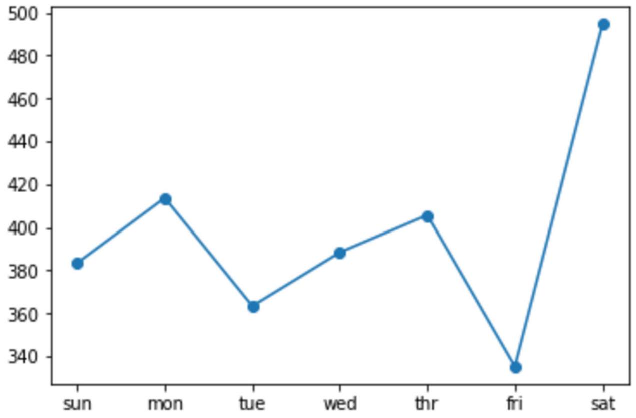

Fig. 7. Line plot of RMSE per day for univariate encoder-decoder LSTM.

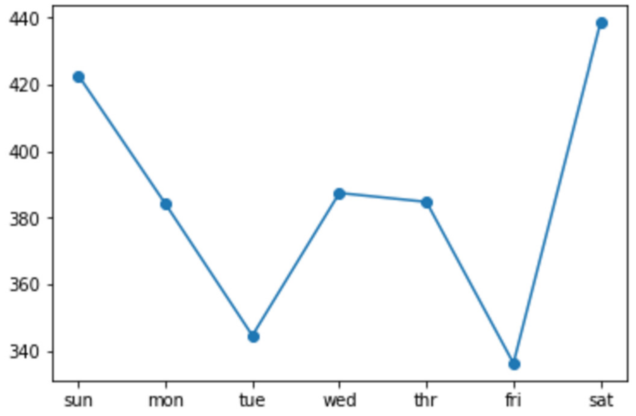

Fig. 8. Line plot of RMSE per day for multivariate encoder-decoder LSTM.

4.4.4. *CNN-LSTM encoder-decoder model with univariate input*

In a hybrid CNN-LSTM model where CNN is used as an encoder and LSTM as a decoder in an encoder-decoder architecture. CNN architecture consists of two 1D CNN layers, the first layer extracts features from the input sequence and the second layer also repeats the same process by focusing on more significant features. In this work, filter size 64, kernel size 3, and activation function rectified linear unit (ReLu) are used in each layer. Max pooling layer reduces the feature size by keeping the most significant features and then flattened into vectors that can be used as input for the decoder. LSTM layer with 200 units followed by a fully connected layer and an n output layer is used in the decoding process. Fig. 9 shows that the model is more stable and skillful with 412 kilowatts RMSE score.

4.4.5. *ConvLSTM encoder-decoder model with univariate input*

In this scenario, Convolutions of CNN are used for each time step as an extension of the CNN-LSTM approach and also known as ConvLSTM. ConvLSTM is used as the encoder for multi-step time series forecasting in encoder-decoder architecture followed by a flatten layer for decoding. ConvLSTM is using convolutions as reading input for the LSTM units. It is used for Spatio-temporal 2D data and can be used in multi-step time series forecasting as a 1D sequence. In the experiment, 14 days of data are split into two time steps of seven days, ConvLSTM then reads on these two time steps and performs convolution on seven days of data at a time. The training dataset is reshaped into 5 dimensions; n samples, 2 timesteps, 1 row, 7 columns, and 1 channel. Experimental results proved that two convolution layers performed better than a single layer. Fig. 10 shows that the model is more stable and skillful with 367 kilowatts RMSE score.

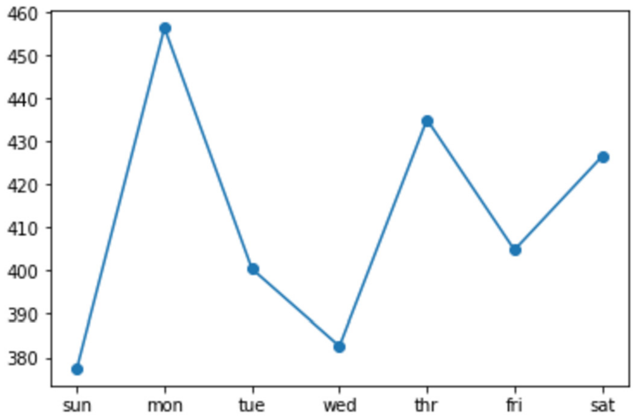

Fig. 9. Line plot of RMSE per day for univariate encoder-decoder CNN-LSTM.

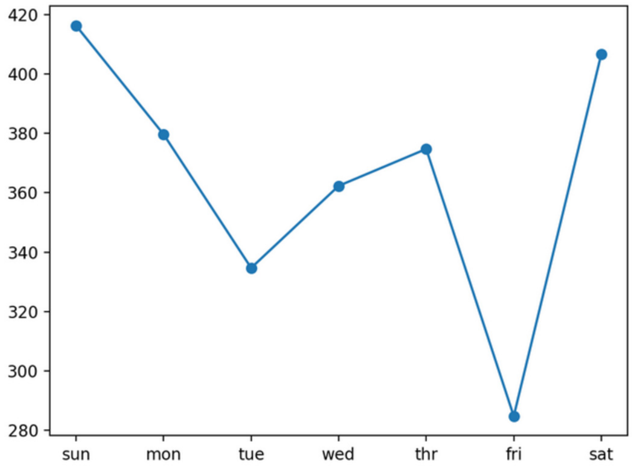

Fig. 10. Line plot of RMSE per day for univariate encoder-decoder ConvLSTM.

4.5. *Discussions*

In this study, the household electric power consumption is explored in two phases. In phase I, of the experiment global active power is predicted. Global active power is the power consumed by appliances other than the appliances mapped to sub-meters. Global active power is the real power consumption i.e. the power consumed by electrical appliances other than the sub-metered appliances. LSTM predicts global active power efficiently with a 0.617 RMSE score.

In phase II weekly prediction of household power consumption is performed in five scenarios. It can be observed from Table 5. As LSTM alone interprets state transitions and internal state, it performed poorly in predicting weekly power use. Encoder-Decoder LSTM with two weeks of multivariate input data fared well in predicting weekly power consumption. Both layers in CNN-LSTM operate independently. CNN retrieves relevant features, which are subsequently fed to LSTM for sequence modelling. The issue with the extraction of significant features by CNN removes the insignificant features which break the training data long sequences. When such irregular data is used to construct sequences via LSTM, accuracy is diminished. Both phases of ConvLSTM operate as a single unit. Convolution functions are utilized in place of LSTM compu-

Table 5
Performance comparison of five scenarios for power consumption multi-step forecasting.

Method	Input Type	Resolution	RMSE
LSTM	Univariate input data	weekly	405 kilowatts
Encoder-Decoder LSTM	Univariate input data	weekly	400 kilowatts
Encoder-Decoder LSTM	Multivariate input data	weekly	387 kilowatts
CNN-LSTM Encoder-Decoder	Univariate input data	weekly	412 kilowatts
ConvLSTM Encoder-Decoder	Univariate input data	weekly	367 kilowatts

tations. This leads in a more efficient training process and more accurate outcomes.

As shown in Table 5, ConvLSTM Encoder-Decoder shows the best performance among all five scenarios according to RMSE values to predict electric power consumption for the week ahead using Social IoT-based smart meter readings. However, as shown in Fig. 10 ConvLSTM predicts completely different values for unusual trends. ConvLSTM is utilizing convolution as part of the input for LSTM and outperformed with 367 kilowatts RMSE score than other approaches.

5. A possible application scenario in the social IoT

The smart environment analyzed in this work is equipped with an ecosystem of smart meter readings that collect data on the electricity consumption of a home. However, the smart system described can be easily integrated into a wider Social IoT architecture. This new environment can associate with the devices used in other heterogeneous smart sensors and objects, both in terms of various components and characteristics but also in terms of appropriate programming languages to interact with them. The possible applications are unlimited, for some the need may certainly be for real-time monitoring of what is happening, while others, leveraging a wider time window, rely primarily on data analysis. An example that falls under the first situation is those applications where the electricity supply is limited, especially in a home setting. In this first situation, to prevent meters from jumping due to a spike in energy consumption, it might be possible to take advantage of the interaction and exchange of information between smart meter readings and, for example, the custom lighting system so that it alerts the user. Through the smart readers it would be possible to have a real-time report of the consumption of the house and as soon as this approach the maximum power that the electrical system can provide, the light, for example, could change color or intensity and thus alerting the user of this excessive consumption. A possible second application scenario in which to analyze a wider time window can allow to manage the energy consumption by relating it, for example, to temperature data. In this situation, we imagine that the temperature reaches a certain threshold and at the same time a certain energy consumption has been reached or it is expected that it can be reached, we can therefore think that the intelligent air conditioning is automatically turned off. Similarly, this intelligent mechanism that oversees and predicts the consumption of all devices in the house, could also suggest turning on some appliances that have been programmed to be turned on during the day, such as the washing machine or dishwasher, when low energy consumption is recorded. In this way, knowing also what the consumption and duration are, it can drive the startup. Furthermore, with an in-depth analysis of actual consumption and daily energy forecasts, it is also possible to obtain feedback if an appliance consumes more energy than normal and, if necessary, report it with appropriate signals.

5.1. Computational complexity of models

To evaluate the performance of the proposed approach regarding the computational complexity, execution time of the models is analyzed. All the experiments are carried out on a 2 GB Dell PowerEdge $T430$ graphical processing unit on $2x$ Intel Xeon 8 Cores 2.4 Ghz machine which is equipped with 32 GB $DDR4$ Random Access Memory (RAM). Table 6 shows the execution time of the models with different kinds of features. Results indicate that the shortest time is consumed by the proposed ConvLSTM model when used with univariate input which is 55 seconds. This time is similar to using the LSTM model with univariate input and vector output. The execution time for other models is higher as compared to the proposed approach which shows the efficacy of the proposed model for energy consumption prediction.

Table 6
Time complexity of proposed approach.

Model	Execution time (sec)
LSTM Models with Univariate Input and Vector Output	55 sec
Encode-Decoder LSTM Model with Univariate Input	65 sec
Encode-Decoder LSTM Model with Multivariate Input	82 sec
CNN-LSTM Encode-Decoder Model with Univariate Input	60 sec
ConvLSTM Encode-Decoder Model with Univariate Input	55 sec

Table 7
Performance comparison with state-of-the-art works.

Reference	Model	RMSE
[42]	Hybrid Greys model	1.30
[31]	CNN-LSTM	0.61
Current	ConvLSTM	0.61

5.2. Validation of proposed approach using EEML 2019 – electricity dataset

To validate the performance of the proposed approach, experiments have been performed on another dataset namely ‘EEML 2019 – Electricity prediction’ [28]. The dataset contains information on a long time series of measurements taken regularly of the instant production power from all sources, including coal, gas, nuclear energy, etc. Consumption shows the desired energy. Except for the date, all columns’ measurements are in megawatts. Continuous measurements from January 2010 through January 2018 make up the training set. For testing, the data for January 2018 to January 2019 are used. Results show that the proposed ConvLSTM Encoder-Decoder shows an RMSE of 207 kilowatts using univariate input data which validates the performance of the proposed approach.

5.3. Performance comparison with existing approaches

The performance of the proposed approach is compared with existing state-of-the-art approaches that perform energy consumption prediction using deep learning models. For this purpose, [31,42] are selected as these approaches also utilize hybrid models of CNN and LSTM. Table 7 shows the performance comparison results indicating that the proposed model produces better results with lower RMSE value than existing works.

6. Conclusion

In an ecosystem of smart devices able to communicate with each other to solve similar problems, the concept of Social IoT is born and developed. In this paradigm, the smart objects are autonomous in their communication with other ones for their need. Nowadays, there is a growing interest in using this concept in different sectors such as transportation, utilities, home automation, and so on. In this study, deep learning models as five different scenarios are utilized to forecast electrical energy consumption in single household analyzing the data obtained by Social IoT-based smart meter readings. In the first phase, LSTM is used to predict Global Active power consumption for each day over 500 hours. LSTM accurately predicts Global Active Power with a 0.617 RMSE value. In the second phase, this research work makes use of multiple deep learning time series forecasting models like LSTM with univariate input and vector output, LSTM Encoder-Decoder model with univariate input, LSTM Encode-Decoder with Multivariate input, CNN-LSTM Encoder-Decoder model with univariate input and finally ConvLSTM Encoder-Decoder. This research work concludes that ConvLSTM Encoder-Decoder outperforms the traditional LSTM and CNN-LSTM models with a 367-kilowatt RMSE value. The ConvLSTM-2D layer extracts the most useful information from the original raw data and converts the univariate single household power consumption dataset into multi-dimensional data, which facilitates the prediction performance of LSTM. A significantly low RSME value shows the effectiveness of the proposed approach for longer time period power consumption forecasting using Social IoT-based smart meter readings. The current study utilizes the historic data for future energy consumption forecasts. In the future, we intend to adopt the proposed approach for making real-time predictions for energy consumption. Further, we intend to introduce a feedback mechanism to reduce the RMSE of the proposed approach for real-world applications.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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