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Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting

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ABSTRACT

Due to global warming and climate changes, buildings including residential and commercial are significant contributors to energy consumption. To this end, net zero energy building (NZEB) has become a progressively popular concept where the annual sum of power generation and consumption is zero. However, occasionally, there exists a mismatching between demand and supply in NZEB due to consumer behaviour and weather conditions disturbing the overall management of the smart grid. To overcome such hurdles, precise prediction of energy usage is a key strategy among others. Therefore, in this study, an efficient hybrid AI-based framework is proposed for accurate forecasting of power consumption and generation that is mainly composed of three steps. Initially, the optimal pre-processing procedure is applied for data refinement. Next, for the spatiotemporal features, a convolutional long short-term memory (ConvLSTM) is used that learns discriminative patterns from the past power knowledge, followed by a bidirectional gated recurrent unit (BDGRU) that extracts on temporal aspects. Eventually, feature descriptors are then passed to multilayer perceptron layers to perform the forecasting. After extensive experiments over the household and photovoltaic energy data, we concluded that our model substantially reduced the errors of 0.012 and 0.045 in terms of mean square error (MSE) on hourly data as compared to the recent state-of-the-art techniques (SOTA).

1. Introduction

Due to the exponential growth of populations, technological advancement, and economies, global energy consumption is rising daily at an alarming rate. In a recent survey, it was reported that over 40 % of energy is consumed in buildings to meet the requirements of consumers [1]. Building construction, weather conditions, and consumer behaviour have a significant impact on entire energy usage. In a conventional grid, due to the unavailability of a proper management system, a huge amount of energy is lost from both the customer and supplier sides [2]. Therefore, the local grid is rapidly upgrading into a smart grid, aiming to supply efficient energy to buildings with constant voltage and at a low cost. Furthermore, to meet energy demand NZEB is considered a favourable solution, where local renewable energy (RE) systems are integrated [3]. On the other hand, the intermittent and unstable nature of renewable energy (e.g., solar energy) can cause severe problems in the power grid by introducing a mismatch between RE generation and demand. The recent statistics released [4] by the South Korean government about power generation is given in Fig. 1. In the year 2017, the total clean energy generated via various sources including waste, bio, the hydro, wind, and solar is gradually increasing due to technological advancement [5]. After eight years most of the building energy in South Korea will generate a huge amount of energy from these resources. Furthermore, in buildings, saving energy is considered an essential component for tackling climate change. To overcome such a problem, a trustworthy anticipation model is the only solution for power management and energy preservation in buildings.

To schedule smartly and satisfy consumers' needs on a federal or local level, precise electricity prediction is a significant component to assist the grid. Also, it can prevent unnecessary power supply and storage. For instance, if a high demand for energy from the consumer side is predicted, then unnecessary usage could occur due to excess power generated by photovoltaics. In contrast, the prediction of inadequate electricity demand may trigger a power outage to occur due to scarce power generation resources [6]. Therefore, a durable plan for power demand and supply should be possible when accurately forecasting energy consumption and generation, reducing costs and providing a convenient way to efficiently operate an entire power grid [7].

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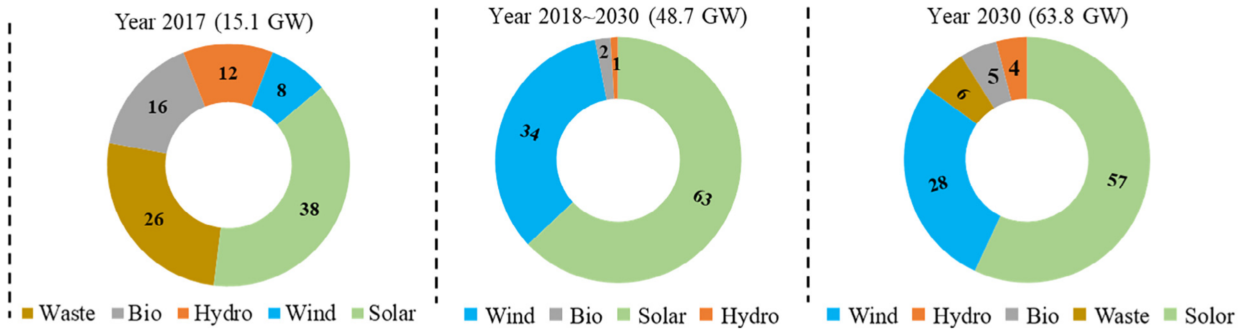

Fig. 1. The latest statistics are collected from the Korean Energy Information Agency [4].

In a smart grid, consumer response is also an important topic for research. A smart grid is responsible for various operations such as storage, demand, and load management. Also, it provides a responsive environment for the exchange of information between consumers and suppliers. Therefore, the autonomous prediction model is highly desirable to improve the current policy and consumer satisfaction. To this end, numerous researchers are developing highly anticipated models for power consumption and generation. However, these approaches are mainly designed to be one-sided; in other words, they can only be used to predict either energy consumption or energy generation. A brief description of these approaches and their flaws are given in the subsequent paragraph.

In recent decades, numerous researchers have performed studies to anticipate RE and electricity consumption [8], where multiple energy management systems and diverse forecasting period horizons have been deeply studied including short, medium, and long-term [9]. Short-term energy forecasting is mainly used for scheduling the transmission among energy sources, consumers, and batteries; whereas, cost determination, power dispatch, and maintenance planning are mostly handled by medium-and long-term forecasting [10,11]. With the rising quantity of smart grid monitoring data and better data mining algorithms, data-driven techniques for estimating RE and electricity load (EL) have attracted researchers' interest [12]. There are two types of data-driven energy forecasting approaches statistical and machine learning (ML) [13]. The main ambition of statistical approaches is to establish mathematical relationships between input and output data [14]; whereas, the Kalman filter [15], autoregressive moving average [16] and Markov chain model [17] have been widely used for energy forecasting. ML approaches (random forest, support vector machine, and fuzzy logic) have achieved incredible outcomes due to their superior capability to map the complicated nonlinear input-output relationship [18,19]. For instance, a study [20] investigated different RE sources, such as solar, wind, and hydro, and empirically proved the efficiency of the artificial neural network for power prediction. Similarly, ML applications and taxonomy have been briefly studied [21] for energy systems, where, based on experiments, the authors analyzed that the hybrid models showed accurate prediction scores. Furthermore, numerous forecasting algorithms have been examined from diverse viewpoints including energy policy, economy, battery storage capacity, and power generation in RE sources [22]. Later, the researcher's attention was diverted to the deep learning (DL) model of its remarkable performance in prediction tasks because of its strong capabilities in recognizing the primary nonlinear characteristics rather than employing handcrafted features [23].

In DL, convolutional neural networks (CNN) and recurrent neural networks (RNN) are widely used for solving numerous problems, particularly energy forecasting problems [24,25]. The learning capabilities of these models are worthy and have a strong potential generalization ability to compare ML and statistical techniques. To efficiently converge the DL models, first, we need to investigate the nature of the RE and EL data, which includes both temporal and spatial features. As previously known, all CNN models have a strong potential to extract spatial information while sequential models have sufficient capabilities to capture temporal features. Therefore, numerous forecasting models exist for RE and EL predictions that explore CNN and the variants of RNN. However, due to the diverse attribute nature effect, the performance of the individual learning model is limited and doesn't meet the requirements as well as not capable to use for establishing an efficient management system between consumer and provider.

After investigating the literature and analyzing the research, we found that the hybrid model had sufficient potential to extract robust, discriminative, and optimal features from historical energy data. To this end, several combinations of models have been developed including CNN-GRU, CNN-RNN, CNN-LSTM, and an autoencoder with BiLSTM. The aforementioned models have strong capabilities to precisely predict RE generation and EL patterns. Although, prediction results obtained from these models still need improvements to bring a trustworthy management system for NZEB. To accomplish this job, we proposed a hybrid sequential learning model ConvLSTM-BDGRU for accurate prediction. The key contributions of this article are as follows:

1. Existing ML/DL models for energy forecasting are particularly designed for power consumption or generation prediction, which do not properly assist the power management systems in smart grids. To solve this problem, a generalized model is proposed that can be used for dual functionalities and provide a convenient way to communicate between supplier and consumer demand, and fulfill the requirements.
2. The performance of the AI-based model entirely relies on data. The publicly available data not exist in a refined format, due to environmental factors and consumer behaviour, the recording devices encounter the problem where the consumption and generation units are largely influenced that contain outliers, missing values, and variant scales that made hurdles in the learning process. To fill this gap, pre-processing is applied, where scrubbing and standardization methods are employed.
3. Photovoltaics (PV) generation data is highly influenced by different factors, and weather condition is one of them. Existing predictive models do not consider weather-related attributes that are not suitable for the unconditional situation and generate predictions with a high error rate. To tackle such conditions, our proposed AI-based model intelligently utilizes weather information and generates accurate results.
4. To verify the generalisability of the model, an extensive experimental results are generated by analyzing various flavours of feature learning techniques and diverse time scales. Further-

more, the performance is compared with SOTA techniques using three evaluation metrics: the MSE, root mean square error (RMSE), and mean absolute error (MAE) using household consumption and PV solar energy datasets.

The remaining sections of this article are categorized as follows: Section 2 is a brief review the existing attempts in energy consumption and generation prediction, while in Section 3 a technical description of the proposed framework is presented. Furthermore, Section 4 covers the implementation detail and comprehensive experimental results over different datasets. Finally, Section 5 provides a summarised description of the proposed work followed by future research directions.

2. Literature review

Several works on energy have been completed with common aims, reducing the usage of energy in the building sector while increasing energy efficiency. Furthermore, the maximum cost-effective relief option is to supply low-carbon energy that can minimize the overall cost and greenhouse gas release at the same time. Regarding enhancing energy efficiency, various researchers are also working on low-carbon energy resources that are considered another significant supportive policy [26]. Wall-fitted solar panels play a major role in decarbonizing energy generation in buildings [27]. Hydropower, heat release from power generation resources and burning can substitute fossil fuels that are mainly utilized for building cooling and heating systems [28]. To enhance the efficiency of energy consumption and allow passive and active buildings, it is necessary to accurately predict future consumption and generate energy. To this end, the literature is mainly categorized into two subsections with detailed information, challenges, and research gaps.

2.1. Energy consumption prediction approaches

For power consumption analysis numerous methods are being developed to examine time series data to obtain more significant statistics and other attributes related to the data. In a forecasting time series, the model forecasts the future value based on historical data [29]. It is a sequence of data that is recorded at equal intervals of time and uses a particular model to forecast the future value in various horizons such as by the minute, hour, week, or month [30]. The assessment of the time series is mainly composed of two steps: initially, the structure and its primary patterns of the analyzed data are extracted, while in the second step, a data-driven model is fitted to the historical data to obtain future predictions. Time series are commonly used for future energy consumption prediction, as buildings are progressively being observed in real-time. Historic energy consumption data can be used for future energy prediction that assists the management team in making new policies. Numerous time series' artificial intelligence (AI) and statistical models have been proposed particularly for energy consumption predictions in a building. A brief explanation of these methods is given in the subsequent paragraph.

Regarding power consumption prediction, statistical approaches are widely studied but only exist in relatively old literature. For instance, a support vector regression (SVR) is deeply analyzed for energy forecasting [31]. Similarly, a study [32] applied an extreme learning machine (ELM) algorithm followed by a wavelet transform. In addition, to take full advantage of ELM, the artificial bee colony method is explored to obtain optimal parameters for further improvement. In commercial buildings, to complete the consumer side demand SVR is applied for short-term forecasting [33]. Later, another statistical approach called gradient boosting was explored for the short-term horizon and provided a comprehensive study of using multiple filters which have strong flexibility rather than the traditional kernel [34]. These models show limited performance due to extracting unmatured features in the case of complex data, therefore, DL techniques are currently the most popular and widely used techniques for these types of data.

Based on deeply studied literature, deep learning models show tremendous performance on time series data; however, their methods are individually designed for either consumption or generation prediction. For example, STLF-LSTM was mainly developed to accurately predict the energy consumed in buildings and to assist the energy management system [35]. Similarly, based on the genetic CNN and the LSTM energy forecasting model was proposed for accurate predictions where extensive experiments are generated over residential and commercial buildings [36]. Another model was introduced using various kernels that significantly minimized the error score, although, on different time horizons, the overall performance was not better due to data complexity [34]. To further boost this work, autoencoder and cluster-based methods were utilized that intelligently extracted features on a high level that meets the demand of consumers in the building [37]. As the energy demand is currently rising due to entire building appliances being reliant on electricity, efficient management of the local energy system is necessary. To deal with such a problem, a novel DL model was proposed for precise consumption prediction of building energy [38]. Similarly, considering the same challenges, a two-phased DL model was introduced for short-term load forecasting to optimize building-related operational strategies [39].

To establish a trustworthy management system for a smart grid, a sequence-to-sequence (S2S) approach was developed that was suitable for only short-term consumption forecasting [40]. To overcome this obstacle, a stochastic model was proposed called FCRMB that obtained a minimum error score on both short and long-term situations [41], but its performance is highly influenced due to certain factors including weather, heating systems, and residential architecture. To cover such a scenario, a hybrid DL model was introduced known as CNN-LSTM which considers additional home appliances variables that play a significant role in the prediction score [42]. Furthermore, another study also focused on various situations and proposed an autoencoder-based explainable AI model SE-AE, that verified its suitability for electrical energy management systems in smart grids [43]. Inspired by building-related factors, a novel hybrid approach was presented M−BDLSTM that reflected two key challenges including cloud conditions and scheduling of energy consumers [44]. This work was further improved with the assistance of CNN-BiLSTM for short-term prediction and compute execution time to prove its adaptability over the smart grid [45]. Next, the individual residential house power analysis was performed using CNN followed by recurrence plots CNN-RP that facilitate consumer demand and distributed power system [46]. To become more efficient a power management system in the smart grid another algorithm was developed SE-AE that evaluates the model from various perspectives and achieved a better score of MSE [43]. Similarly, another research article also contributed a lot regarding energy prediction for residential as well as commercial building management, where an optimized DL model CNN-LSTM-AE was presented that intelligently encode and decode the input data, resulting accurate prediction score [47].

Sometimes in forecasting models there exist non-linearity between sequential input and output that distributes the overall performance during testing. To address such a hurdle, a novel dual fusion network was proposed CNN-GRU however, such a model was only designed for short-term purposes and secondly, GRU has limited capability to extract complex patterns [48]. Similarly, the attention-based model CNN-LSTM-MHA was also explored for time series forecasting data that shows remarkable performance for long-term prediction, and a high error score is achieved when tested for a short time scale [49]. Such performance is enhanced and integrated dual novel DL model DB-Net for an encoder and a decoder that achieved incredible performance on a household dataset [38]. Limited work has been found that has generalization capability and a dual sequential-based model that extracts Spatiotemporal features from the initial model and then temporal information is captured from another one. For instance, CL-Net was introduced for dual functionalities including battery health as well as energy consumption prediction [50]. Next, CLSTM-BLSTM was proposed for efficient forecasting and computing time complexity to verify its adaptability on edge devices [51]. Later, an ensemble algorithm with a sequential model was developed to further reduce the error prediction rate [52]. All these researchers' efforts had limited performance in the case of an irregular trend of data and were unable to predict the energy for the demand side to efficiently establish the concept of NZEB.

2.2. Energy generation prediction approaches

In recent decades, energy consumption prediction researchers have shifted their consideration toward RE for assessing power generation. Currently, smart buildings are being developed where different sources of energy, such as solar, wind, and hydropower are widely used due to their renewable and clean nature. In this study, we are mainly interested in solar power generation prediction that fully relies on environmental factors including wind direction and its speed as well as weather condition. These uncontrollable parameters create hurdles in the prediction. Numerous approaches for power generation prediction have been developed, which are briefly discussed in the subsequent paragraph.

Solar panel energy is clean because it does not release carbon or other toxic gases. With this beneficial property and eco-friendly technology, many people who live in urban neighborhoods have installed solar panels in their homes. Ultraviolet radiation is the most significant parameter for photovoltaic energy in various time scales. Numerous data-driven models, including ML and DL, have shown incredible performance; however, there is still space to further minimize the error score when perfectly managing the energy system. For instance, in the study, various CNN, SVR, and sequential learning models were deeply analyzed for power generation prediction [53]. Furthermore, well-known traditional learning approaches such as random forest, XGboost, and gradient boost were applied to evaluate their performance [54]. Similarly, another study also investigated decision trees, support vector machines, and artificial neural networks for the prediction of solar panel heat [55]. Moreover, short-term solar panel power generation predictions have mostly been done with the assistance of CNN [56]. Later, to minimize the prediction error score, the researchers explored the variants of RNN which were convincing and reliable approaches [57]. After an extensive study of the literature, we concluded that local energy systems are still trying to find an AI-based intelligent model that accurately predicts energy consumption as well as generation individually for smooth transmission of energy between supplier and consumer. Considering this point, we found the following research gaps in the existing literature, which are addressed in this study.

a) Renewable resources provide clean energy however, this energy depends entirely on weather conditions such as rain, etc. Therefore, its accurate prediction is necessary for power management.
b) Energy consumption relies entirely on consumer behaviour which varies over time. Therefore, its accurate prediction is important for power balancing.
c) Mainstream approaches are mainly considered for either consumption or generation predictions; however, for efficient power management, both predictions need to be made simultaneously.

3. Proposed framework

RE and EL predictions are very significant for efficient management between providers and consumers. However, accurate prediction of energy is still a challenging job due to the unorganized scheduling of consumption by consumers, missing or noisy data collection, and volatile weather situations. To assist mediate these conditions, numerous approaches have been established to predict power load and generation, as briefly discussed in Section 2. The power management department is still finding a trustworthy and generalized model which can be used for dual purposes, generation and consumption forecasting. To fulfill this requirement we present a generalized DL model as shown in Fig. 2. The technical information about the main components of our model is provided in the following subsections.

3.1. Energy data collection

This step is very crucial, where two different types of data are collected from various sources i.e., solar panels and houses. Regarding energy consumption-related data, the wires in the consumer building floors are interconnected with a mainboard. Next, the individual smart meter is positioned in a separate building section that usually counts energy units by the minute. This constant energy data reading is directly influenced by consumer behaviour, environmental conditions, and circuit fuses, that create noise, redundancy, and an outlier in the data. On the other hand, energy generation data is also influenced by the weather, hardware, and solar panel. For example, due to electricity load-shedding, the weather forecasting device could suddenly turn off, or sometimes, faults occur in the hardware, such situations disturb the weather attribute information during the data collection. Similarly, in the case of solar power generation, if there is dust or a shadow on the panel, then it will not generate energy with the required voltage, which can cause the generation data to go up and down significantly, creating huge variations in the data. To overcome these issues in the data, it is necessary to refine the data before passing it on to the DL model for prediction. A detail of the pre-processing mechanism followed in this study is given in the next subsection.

3.2. Energy data pre-processing

Data pre-processing is a significant step for any DL model to intelligently learn from refined data and make accurate outcomes/predictions. In this study, the data used for experiments initially existed in a raw format and contained uncertainties such as missing values, redundancy, noise, and high variation. To overcome such ambiguities in data various pre-processing methods are used to make clean energy generation and consumption data before transferring them to the proposed model. To normalize and remove the outliers in data, a moving average filter and standardization techniques are applied to smoothly converge into a DL model. Furthermore, the substitution method is employed where null values are replaced by their preceding period values. There are several attributes in the dataset where each variable has its own set of scale ranges that made it difficult to tune the model for a specific task. As DL models learn large numbers of parameters when given input data, values have a large and diverse range. Moreover, due to such reasons, the trained model becomes volatile and yields an unsatisfactory performance. On the other hand, if

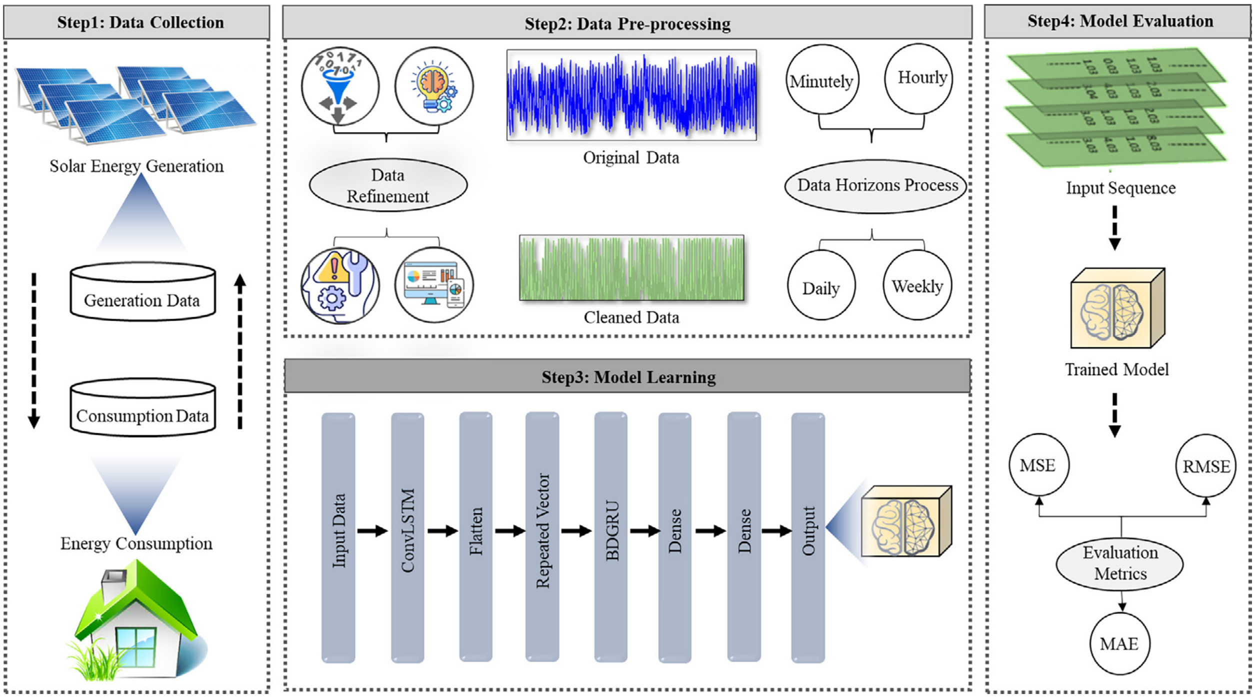

Fig. 2. The generalize proposed framework for the prediction of energy consumption and generation prediction, is mainly composed of four steps: initially, the required data is collected from various sources which are then passed to a pre-processing step that efficiently polishes the data and distributes the data into different time resolutions including minutely, daily, weekly, and hourly. Next, the refined time series data is forwarded to the proposed model for training that intelligently learns discriminative features. Finally, the model is tested and evaluated using numerous metrics.

there is a high difference in variable values output makes the feature learning procedure unstable and obtains a large error score for prediction. The above discussion exhibits that scaling of the data is more important for getting the right prediction for future data. Therefore, we normalized all unscaled data are arranging them between 0 and 1 as shown in Fig. 3.

To check the strength of the proposed model, we applied the data horizons process, which set the energy data into four different time resolutions, per minutely, daily, hourly, and weekly. However,

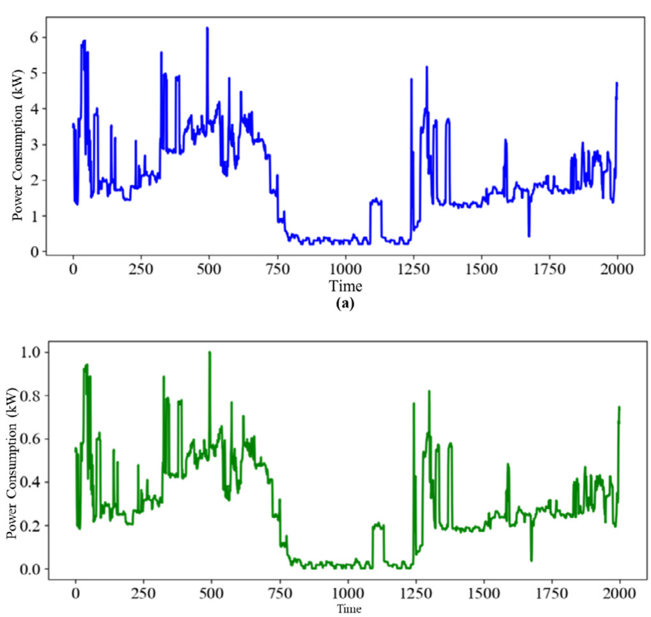

Fig. 3. Visual representation of a historical household energy consumption dataset where (a) depicts the actual data while (b) illustrates normalized data.

in the literature, most of the researchers considered hourly data; therefore, only hourly data is compared in the experimental section.

3.3. Spatiotemporal features learning via ConvLSTM

The main obstacle in fully connected LSTM is processing spatiotemporal information during the transformation of the data from input to state and state to state. More specifically LSTM is considered an effective technique to manage the temporal relationships in data. To learn both spatial and temporal features, a ConvLSTM is applied rather than an LSTM, where a convolutional operation is performed internally and has a strong capability to learn spatiotemporal features. In this study, multiple layers of ConvLSTM are stacked by encoding time series data, which not only extracts spatiotemporal features and also shows remarkable performance in predictions. Regarding the learning process, a ConvLSTM has a strong complementary power to manage a more complicated sequence of data, as compared to a conventional LSTM. The fundamental structure of a ConvLSTM is shown in Fig. 4. In the RNN architecture multiplication process is performed internally, while in ConvLSTM layers convolutional operation is executed during sequential learning. Furthermore, it has a powerful ability to decide whether the current information needs to be learned or ignored from the preceding state. The whole process performed in a ConvLSTM is described in Eqs. (1) to (5).

$$i_t = \delta(W_{ix} * x_t + W_{ih} * h_{t-1} + W_{ic} \odot c_{t-1} + b_i) \tag{1}$$

$$f_t = \delta(W_{fx} * x_t + W_{fh} * h_{t-1} + W_{fc} \odot c_{t-1} + b_f) \tag{2}$$

$$o_t = \delta(W_{ox} * x_t + W_{oh} * h_{t-1} + W_{oc} \odot c_{t-1} + b_o) \tag{3}$$

$$g_t = tanh(W_{gx} * x_t + W_{gh} * h_{t-1} + b_g) \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad h_t = o_t \odot \tanh(c_t) \tag{5}$$

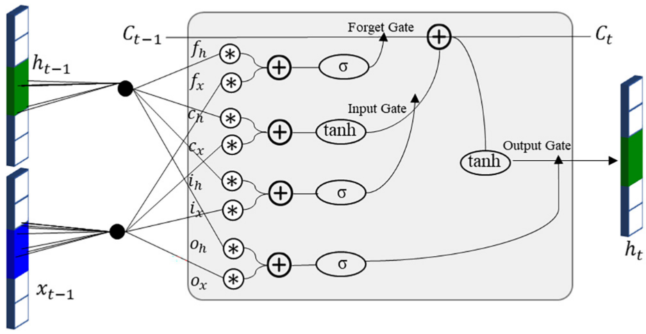

Fig. 4. The basic architecture of a ConvLSTM for spatiotemporal feature learning.

where element-wise and convolution operations are denoted by ⊙ and * while other necessary functions such as hyperbolic and sigmoid functions are presented by tanh and δ. Similarly, the total time step in ConvLSTM is shown by 't' whereas i_t, f_t, o_t, g_t demonstrates the input gate, forget gate, output gate, and adjustment gate. Additionally, the three variant states such as input, cell, and hidden are represented by x_t, c_t, and h_t. There are two different types of input tensors extracting variant features. For instance, i_t, f_t, o_t, x_t, c_t, and h_t where the first three are used for temporal features while the last two are for spatial information. Due to the usage of both spatial and temporal features, experimental results proved that considering a ConvLSTM for the sequential learning mechanism is the right decision because it showed a significant contribution to both RE and electricity load forecasting.

3.4. Temporal features learning via BDGRU

Energy prediction is a regression-based task associated with time series. In the current study, we had historical energy data and need to predict different horizons; therefore, forward and backward information learning is significant to get a minimum error score. To this end, BDGRU is applied for both energy generation and consumption forecasting problems. RNN is particularly designed for sequence data processing. However, there exist some weaknesses in RNN which are widely faced by researchers in cases of long-term dependency problems, such as exploding and vanishing gradients. To handle such problems, two traditional RNNs are introduced, i.e., GRU and LSTM. These networks can learn long-term features with the assistance of gates including input, forget, and output gates. Unlike LSTM, GRU is a computationally less complex architecture that contains only two gates that exist, including the update and reset gates with no memory unit. Previous studies revealed that the performance of GRU is better than that of LSTM. The structure of the GRU mainly contains two gates where each has its functionality, i.e., the update gate (z) indicates which information can be held to the subsequent state, while the reset gate (r) indicates how to fuse the earlier state information to the new input data. The following are the formulas from (6) to (9) that represent the output and state values in GRU.

$$z_t = \sigma(W_Z * [x(t), h(t-1)]) \tag{6}$$

$$r_t = \sigma(W_r * [x(t), h(t-1)]) \tag{7}$$

$$\hbar_t = \sigma(W_Z * [x(t), (r_t * h(t-1))]) \tag{8}$$

$$h_t = (1 - z_t) * h(t-1) + z_t * \hbar_t \tag{9}$$

where activation function, input, and previous output are represented by σ, x_t, and h(t-1), while the weights of update, reset, and output gates are denoted by $W_Z, W_r, andW_h$ respectively.

In this paper, a BDGRU is applied composed of two conventional GRUs, that handles the input tensor from dual directions and then combine their resultant outcomes. The baisc architecture of BDGRU is given in Fig. 5, where sequential patterns learns in both forward and backward directions.

4. Experimental results

This section is mainly composed of four parts: initially, we provided a detailed implementation and optimal hyperparameters for the training procedure. Next, a brief description of the datasets followed by evaluation metrics was presented. In the third part, the results obtained via the proposed model were compared to existing work on both datasets. Finally, ablation studies were conducted to show the complementary ability of the proposed model.

4.1. Setup

To implement the proposed forecasting system, we needed basic software and hardware requirements including python (3.8.5) programming language, Keras framework (2.5.0), Tensorflow (2.5.0), window 10, AMD Ryzen 9 3900X, 12-core processor, GeForce RTX 3090, and 48.0 GB RAM. Furthermore, regarding the data preparation for the experiments, the dataset was split through the holdout technique, the dataset is split into 70 % and 30 % for training and testing. All the experiments were conducted using batch size (16), optimizer (Adam), and epochs (100).

4.2. Datasets and protocol

To verify the generalization ability of the proposed model and to establish efficient management between supplier and consumer, two datasets were used related to consumption and generation.

4.2.1. Household energy consumption

This dataset is publicly available on the official site of the UCI repository. The energy consumption data was recorded for four years from 2006 to 2010. There were a total of 2,075,259 samples, where missing data is counted 25,979 becomes 1.25 % of total instances. Furthermore, the entire data is collected from a building situated in France, where one-minute consumption data is countered. In Fig. 6 global active power shows the microwaves. total energy consumed by sub-metering 1,2, and 3 where the basic unit is Watt-hour. In the active power, the maximum and minimum values were 11.12 and 0.076 in kilowatts. After deeply analyzing the data we found that sub-metering 1 counted more units which means more appliances were used such as dishwashers. The various resolution of data is given in Fig. 7.

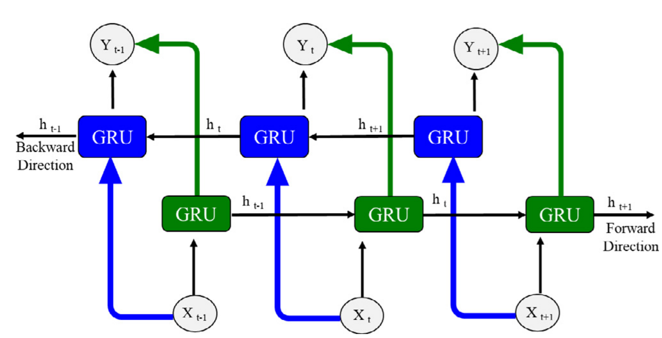

Fig. 5. Block diagram for BDGRU that learns in both forward and backward directions.

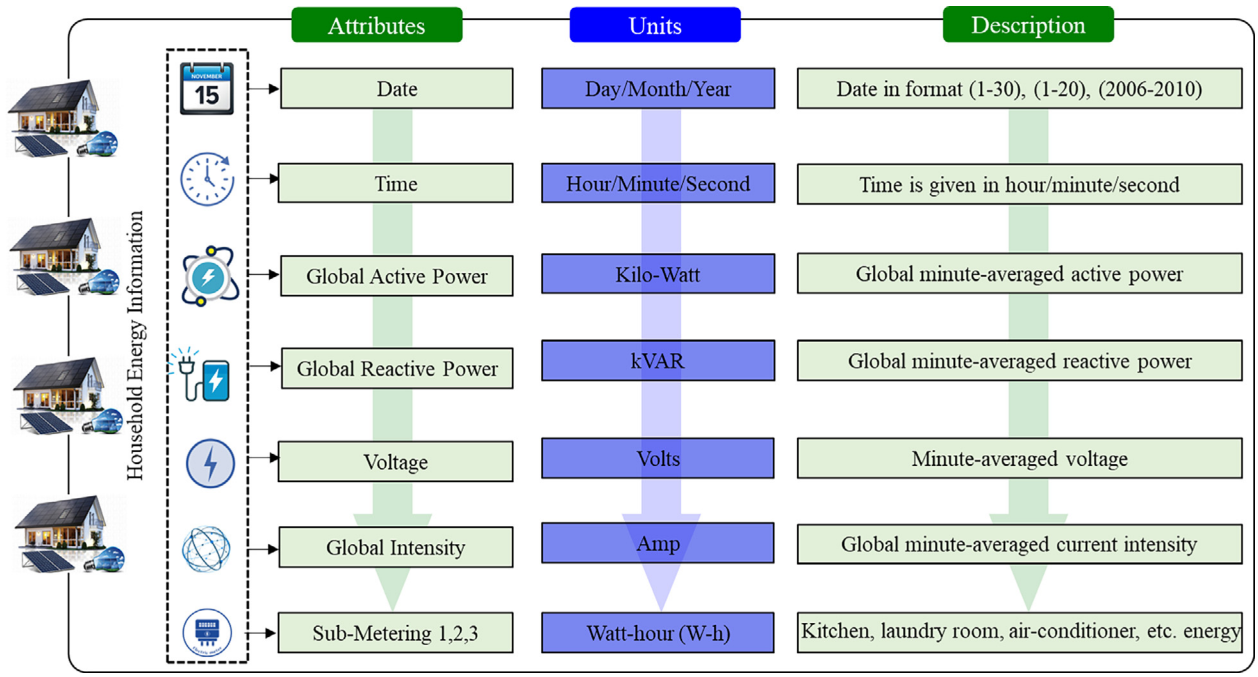

Fig. 6. A brief description of the household energy consumption dataset including attributes, units, and a summary.

4.2.2. PV energy generation

Most of the existing works are related to either consumption or generation power prediction. While in this study, a generalized model is proposed for dual functionality. This dataset is mainly collected from the famous city known as Alice Springs located in Australia where a PV system (DKASC) is installed which has 26.5 kW.

The weather-related information is given in Table 1, while the solar-related details are presented in Table 2, while. Since the year 2010, the counter device was recorded after every-five minutes, where an observed value is considered on each point. Regarding the data splitting, from 1 June 2014 to 31 May 2015 were taken for model training, while from 1 June 2015 to 12 June 2016 were

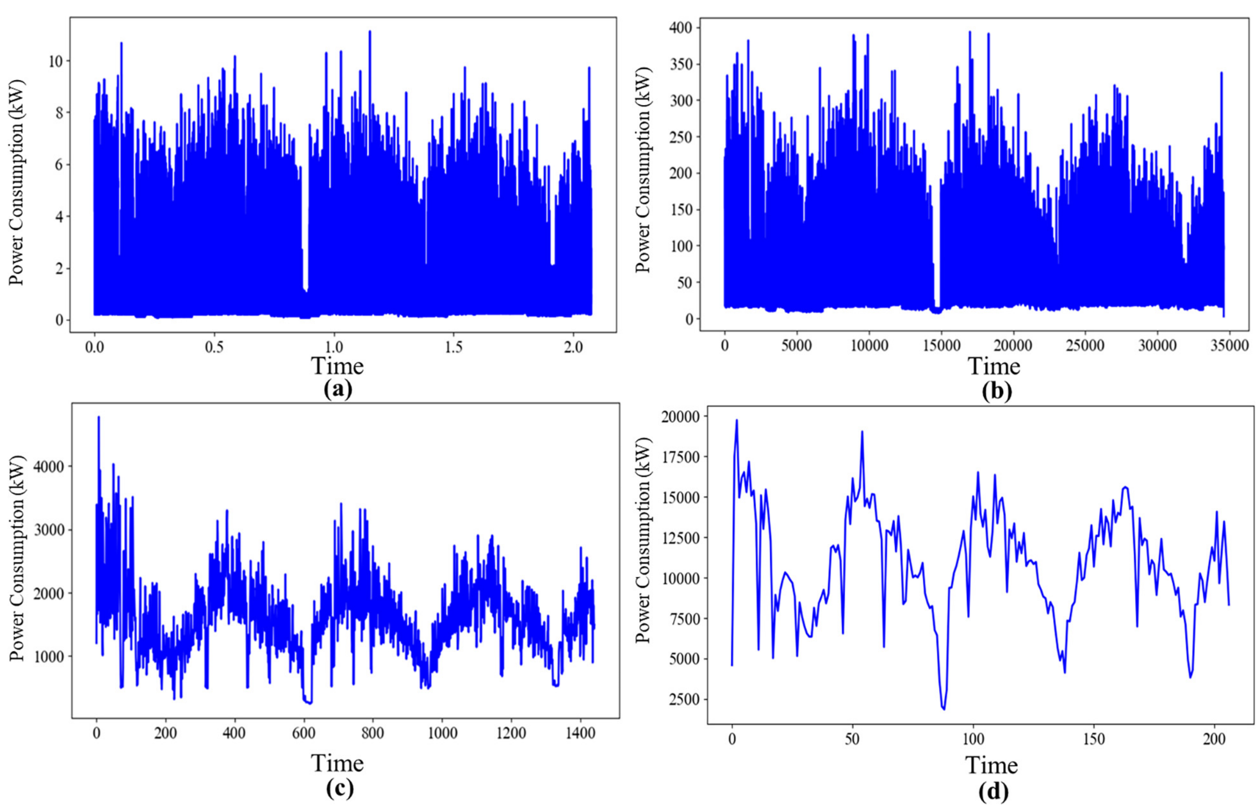

Fig. 7. Different data horizon representations of the benchmark household energy consumption dataset (a) minutely data (b) hourly data (c) daily data (d) weekly data.

Table 1
Detailed statistical analysis information of the PV energy generation dataset.

Attributes	Mean	Std	Min	Max	Description
PV Power	3.940	5.280	0	18.562	The output power of the PV system
Wind Speed	2.284	1.389	0.298	43.78	Speed of the wind in m/s
Weather Temperature	20.942	9.875	−3.085	44.194	The temperature in Celsius
Weather Relative Humidity	36.672	23.138	3.125	101.889	Humidity in percentage
Global Horizontal Radiation	264.436	359.471	1.139	1390.946	GHR in w/m^2
Diffuse Horizontal Radiation	54.008	90.110	0.318	718.653	DHR in w/m^2

Table 2
The technical specifications detail the PV system.

Specification	Unit	Value
Array Rating	kW	26.52
Panel Rating	W	170 W
Number of Panels	–	156
Panel Model	–	Eco-kinetic ECOKES 170 M
Array Area	m^2	199.16
Type of Tracker		ADES 5F-27 M, dual axis
Inverter Size/Type	–	3*9 kW, SMA SMC 9000TL-10
Installation Completed	–	3 Mon, Aug 2010
Array Tilt/Azimuth	–	Fixed. Tilt = 20°Azimuth = 0°

utilized for testing purposes. Both training and testing were containing weather attributes and the output of the PV power of 365 and 378 days respectively.

4.2.3. Evaluation protocol

Once the regression model is trained, the next step is to evaluate its strength via some commonly used metrics including MSE, RMSE, and MAE. The formulas of these metrics are given in Eqs. (10) to (12).

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2 \tag{10}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2} \tag{11}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i| \tag{12}$$

In the above evaluations formulas, y_i denotes the variable for (N) times predictions which obtain samples from energy consumption while y_i represents the observed values. MSE refers to the average square error which evaluates the difference between the estimated and observed values while the RMSE score is obtained by taking the square of the MSE. Similarly, MAE computes the mean absolute between two variables.

4.3. Analytical experimental results

In this section, the results obtained via the proposed model are briefly discussed which reflects its strength. Usually, power management systems in smart grids required a balance between the consumer and supplier. Therefore, in this research, both consumption and generation datasets are extensively evaluated to assist the local smart grid and improve the NZEB performance. The recorded energy data from the demand and provider sides contain abnormalities. For instance, a circuit and hardware malfunction, as well as various environmental condition largely influences the data. To deal with such a problem a preprocessing step is very crucial to overcome the ups and downs of data. Despite these facts, energy generation resources specifically photovoltaic entirely depend on solar radiation so weather situation is also an important factor, and considering its attributes plays a worthy role in prediction. Based on the above circumstances, a hybrid AI-based framework is proposed which is mainly composed of two core modules such as ConvLSTM and BDGRU. The first module extracts Spatio-temporal features while the other one only focuses on sequence information. The actual and prediction graph of the proposed model is given in Fig. 8, while the outcomes of both consumption and generation datasets are given in Fig. 9.

4.4. Comparison with SOTA methods

In this section, the scope of the proposed model was evaluated in two different ways. Initially, the prediction results obtained through the proposed model were compared with an existing attempt on both consumption and generation datasets. Next, a comprehensive ablation study is also conducted in subsection (4.5) to verify the significance of the empirical outcomes against others DL models.

4.4.1. Household energy consumption

Regarding the energy consumption of the building, this dataset is very famous therefore most of the previous studies used it for experimental purposes. Mainstream approaches developed numerous strategies and obtained good performance however, further improvement is highly necessary. To this end, a novel hybrid sequential-based model was proposed, where a remarkable performance was obtained on the same dataset to conduct fair comparisons. On top of the proposed model, we assessed our results

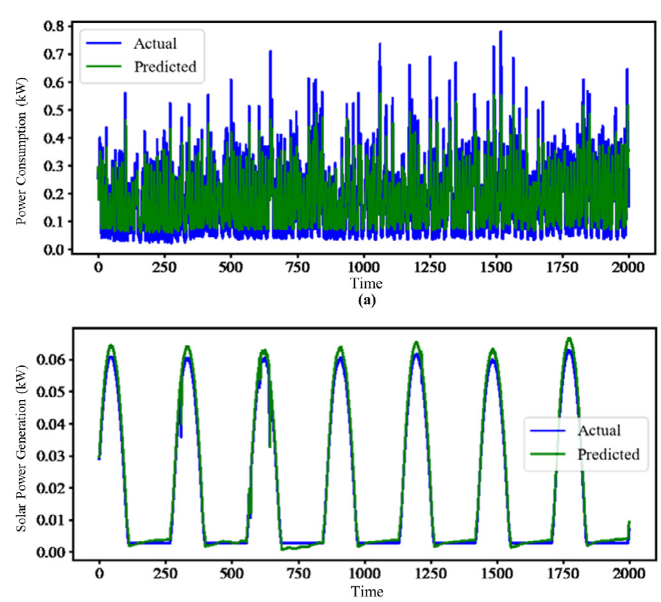

Fig. 8. Actual and predicted visualized graph for electricity load consumption and power generation using (a) household energy consumption and (b) PV energy generation.

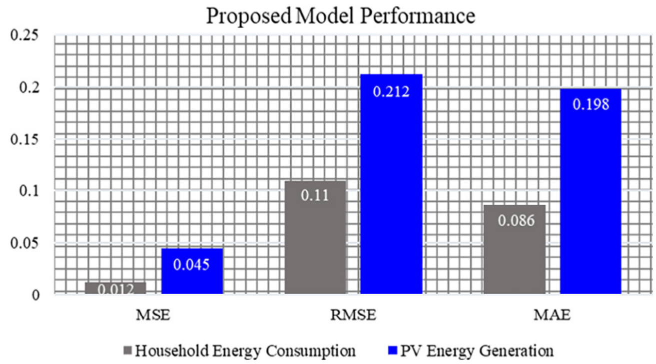

Fig. 9. The prediction performance of the proposed model over household energy consumption and PV energy generation datasets.

with 14 recent models that mostly followed the hybrid approach to get more significant features from the given sequential data. Furthermore, according to the literature studies researchers used hourly data resolution for predictions therefore, we considered the same resolution for our quantitative results to perform a fair comparison as mentioned in Table 3. Due to a discriminative, representative, and robust features extraction mechanism we marginally improve the prediction score is 0.012, 0.110, and 0.086 for MSE, RMSE, and MAE, while the runner-up obtained 0.015, 0.122, and 0.088 for MSE, RMSE, and MAE. The comparative analysis verifies that our hybrid strategy efficiently minimizes the forecasting error and is suitable for the development of the NZEB.

4.4.2. PV energy generation

Solar power is a popular renewable source that provides clean energy, saves human life from many hazardous diseases, and is beneficial for the state economy. Nowadays, most countries installed PV plants and obtain energy on a large scale. However, high-level infiltration of PV power effect brings certain challenges including meteorological situations, installation cost, and intermittency of power generation. To overcome these challenges AI-based model is a unique solution to forecast the PV power in an accurate way to assist the smart grid on the management level. Therefore, in this study, a generalized model is proposed that efficiently works for both consumption as well as generation prediction. To the best of our knowledge, the PV dataset is not widely used therefore the results are compared with a single SOTA method. They followed a hybrid model comprised of wavelet packet decomposition and LSTM (WPD-LSTM), where after extensive analysis they obtained the average score of MSE and RMSE is 0.0555 and 0.2357. While through the proposed hybrid strategy, we beat it on margin scores

Table 3
Performance comparison of the proposed model with SOTA methods over household energy consumption dataset.

Method	MSE	RMSE	MAE
S2S [40]	–	0.625	–
FCRMB [41]	–	0.66	–
CNN-LSTM [42]	0.355	0.596	0.332
SE-AE [43]	0.38	–	0.39
CNN-M−BDLSTM [44]	0.31	0.56	0.34
CNN-BiLSTM [45]	0.29	0.54	0.39
CNN-RP [46]	–	0.79	0.59
CNN-LSTM-AE [47]	0.19	0.47	0.31
CNN-GRU [48]	0.22	0.47	0.33
CNN-LSTM-MHA [49]	0.26	–	–
DB-Net [38]	0.016	0.127	0.092
CL-Net [50]	0.015	0.122	0.088
CLSTM-BLSTM [51]	0.105	0.324	0.311
M−LSTM [52]	0.109	0.33	0.309
Proposed	**0.012**	**0.110**	**0.086**

i.e. MSE and RMSE of 0.045 and 0.212 which verifies the effectiveness as shown in Fig. 10.

4.5. Ablation studies

In this research, a generalized model was proposed; therefore, ablation analyses were performed on both datasets to fairly compute the prediction strength. For optimal model selection, several DL models with various setups were evaluated during the experimental work. The main purpose of generating comprehensive results was to make sure which model extracts more prominent features and gives a minimum error score in terms of MSE, RMSE, and MAE. Tables 4 and 5 represent the quantity results on both household energy consumption and PV energy generation datasets, using numerous time frames such as minutely, hourly, weekly, and daily. A detailed description of the analysis is provided below:

4.5.1. Household energy consumption analysis

In the literature study, researchers were interested in extracting spatial and temporal features from time series data. For this, convolutional layers were widely explored for an encoder that could learn spatial patterns while a sequential-based network was applied for decoding that extracts temporal features. Inspired by such a strategy, a ConvLSTM was investigated that could obtain both spatiotemporal patterns from a given sequential data and achieve good results. Next, GRU was evaluated that could learn temporal information using the forward propagation method, where the prediction score seemed better. After knowing the performance of these models, experiments were conducted on its BDGRU that gave a minimum error score as shown in the tabulation. Finally, after a deep study, we concluded that ConvLSTM and BDGRU show incredible performance in various domains, particularly in time series. Motivated by its tremendous achievements, we tuned it for energy forecasting by using ConvLSTM as the encoder components and BDGRU as a decoder. After deeply investigating a hybrid model over different resolutions, consistent performance is obtained. Based on performance, we chose it as the proposed model.

4.5.2. PV energy generation

Mainstream approaches designed AI-based models for a specific task that gave incredible results. In this study, our learning strategy was different; the proposed model was used for dual purposes i.e. energy consumption and generation. Furthermore, existing attempts in the forecasting domain mainly performed ablation studies on one dataset to compute the strength of the model. In contrast, a comprehensive ablation analysis is delivered in terms of models and data to verify the generalization ability of the proposed model. Here, numerous sequential model analyses with dif-

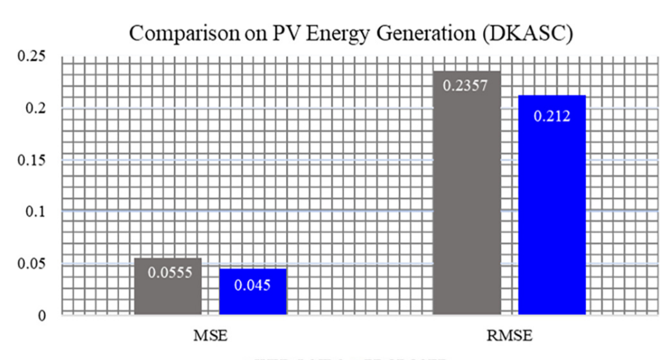

Fig. 10. Performance comparison of the proposed model with the SOTA method over the PV energy generation (DKASC) dataset.

Table 4
Experimental results household energy consumption dataset using numerous time scales.

Method	Minutely		
	MSE	RMSE	MAE
GRU	0.121	0.348	0.289
BDGRU	0.113	0.336	0.266
ConvLSTM	0.078	0.279	0.195
Proposed	**0.049**	**0.221**	**0.138**
		Hourly	
GRU	0.099	0.315	0.143
BDGRU	0.085	0.292	0.124
ConvLSTM	0.041	0.202	0.098
Proposed	**0.012**	**0.110**	**0.086**
		Daily	
GRU	0.096	0.310	0.141
BDGRU	0.081	0.285	0.122
ConvLSTM	0.038	0.195	0.096
Proposed	**0.011**	**0.105**	**0.083**
		Weekly	
GRU	0.109	0.330	0.279
BDGRU	0.094	0.307	0.259
ConvLSTM	0.056	0.237	0.167
Proposed	**0.024**	**0.155**	**0.119**

Table 5
Experimental results on PV energy generation dataset using numerous time scales.

Method	Minutely		
	MSE	RMSE	MAE
GRU	0.285	0.534	0.518
BGRU	0.217	0.466	0.427
ConvLSTM	0.098	0.313	0.287
Proposed	**0.051**	**0.226**	**0.210**
		Hourly	
GRU	0.278	0.527	0.511
BGRU	0.197	0.444	0.422
ConvLSTM	0.096	0.310	0.283
Proposed	**0.045**	**0.212**	**0.198**
		Daily	
GRU	0.272	0.522	0.504
BGRU	0.193	0.439	0.415
ConvLSTM	0.091	0.302	0.274
Proposed	**0.041**	**0.202**	**0.183**
	Weekly		
GRU	0.268	0.518	0.501
BGRU	0.191	0.437	0.412
ConvLSTM	0.089	0.298	0.270
Proposed	**0.038**	**0.195**	**0.179**

ferent time scales were conducted. In the first experimental attempt, instead of CNN a ConvLSTM was investigated the intelligently encode the input data and extract spatiotemporal features because, in the architecture, a convolutional operation was performed internally. As mentioned in Table 5 it gives satisfactory results on overall resolutions. Similarly, for temporal learning GRU was evaluated on a diverse setup of data, where we also showed a convincing performance. After that, the BDGRU model was evaluated, which also provided a convincing performance over various resolutions. Finally, inspired by the hybrid mechanism performance, ConvLSTM-BDGRU was deeply analyzed for short and medium-time scale predictions where they gave minimum error scores as compared to the previous models; therefore, we consider it to as a proposed model.

5. Conclusions and future direction

Efficient energy management is the key objective of the smart grid; therefore, energy generation and consumption are essential to make sure adequate energy to consumers. To achieve this goal, a generalized predictive model is highly desirable that accurately predicts both energy consumption and generation. To ensure efficient power transmission among consumers, solar power plants, and smart grids, this paper presented a sequential knowledge-based model composed of four major steps: (i) initially, the historical data from consumption (building) and generation (solar) are accumulated for the prediction purpose. (ii) Next, pre-processing is applied over collected energy data to refine them before forwarding them to the next layer (iii) In the third step, an AI-based model is proposed where to extract Spatio-temporal features a ConvLSTM is employed while for sequential learning a BiGRU is applied (iv) finally, the trained model is evaluated on testing data in terms of MSE, RMSE, and MAE, to figure out the trained model ability.

Regarding the trustworthy model selection, a comprehensive experiments were conducted, where various learning techniques were investigated over a different way of dataset settings including minutely, hourly, daily, and weekly. These careful ablation analyses demonstrated that the proposed model obtained remarkable prediction scores on an hourly resolution. The error values were attained of 0.012 MSE, 0.110 RMSE, and 0.086 MAE on household energy consumption, while on PV energy generation we got 0.045 MSE, 0.212 RMSE and 0.198 MAE forecasting scores. Furthermore, the comparative analysis verified that the proposed model outperforms when SOTA. Hence, we developed an AI-based model that was suitable for online energy prediction and could be used in local power systems. The proposed model is particularly designed for short-term single-step forecasting and cannot be used for long-term prediction which is the main weakness.

In the future, we aim to develop such a model that has multi-capabilities including short, medium, and long-term forecasting. Furthermore, we will mainly focus on model size and its execution time to enable it for edge devices that operate real-time predictions.

Authors Agreement Statement

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

Data availability

The authors do not have permission to share data.

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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