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ARTICLE

Smart Load Forecasting and Load Scheduling in Agriculture Irrigation Using Deep Learning Techniques

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ABSTRACT: Agricultural irrigation consumes a large share of electricity in rural areas, creating predictable peak conditions on distribution systems that can lead to grid instability and unreliability. Classic load-forecasting and scheduling methods are time-consuming and unable to respond rapidly to fluctuating irrigation demand. Additionally, most traditional methods require a stable internet connection to function and therefore cannot readily adapt to seasonal changes or crop-specific irrigation requirements. This creates inefficiencies in energy consumption and inconsistencies in water delivery to consumers. To reduce these drawbacks, this research proposes a framework for irrigation forecasting and dynamic scheduling for agricultural systems. A hybrid deep-learning algorithm combining convolutional neural networks (CNN), bidirectional long short-term memory (BiLSTM), and particle swarm optimization (PSO) was developed. The CNN component identifies spatial features from historical electricity consumption, soil moisture, weather data, and crop growth-stage information to map when and how much water is needed. The BiLSTM component captures temporal trends in irrigation demand predicted by the CNN. Finally, the PSO component reduces simultaneous agricultural load demand and constrains scheduled demand within a predefined grid-capacity threshold, helping mitigate overloading risks in constrained supply systems. This integrated approach supports improved energy efficiency and agricultural sustainability through better irrigation practices, enhanced management of rural power systems, and increased reliability of irrigation services.

KEYWORDS: Agricultural irrigation; load forecasting; CNN-BiLSTM-PSO; agricultural irrigation; energy-efficient scheduling; rural electric grid

1 Introduction

The problem of energy management in contemporary agricultural systems, especially the irrigation networks in rural areas, has become an area of major research owing to the augmentation of electricity needs, climate change, and the limitations of the distribution grid. The irrigation pumps in the agricultural regions form one of the biggest controllable loads in the areas, running mostly at peak load at the same time. The net effect of this concentrated demand is that it leads to voltage instability, feeder congestion, overloading of transformers, and inefficient use of the generation resources. Therefore, achieving stability in the water supply and at the same time maintaining the grid's stability involves working together to have load forecasting and optimal scheduling systems [1]. The inherent characteristics of the electricity demand in agriculture are the seasonal characteristics of the environment, like rainfall, variability in temperature, moisture availability in soil, crop growth, and water storage capacity. Long-term and medium-term demand estimation has used traditional statistical forecasting methods due to the simplicity and interpretability, furthermore [2]. Nonlinear dependence and sudden change in demand: Regression-based and classical time-series models are based on the assumption of linearity and stationarity, which restrict their application in modelling nonlinear dependencies and sudden shifts in demand that are frequently observed in agricultural load patterns driven by irrigation machine learning-based forecasting To get around these limitations, machine learning-based forecasting has been proposed in the context of agricultural load prediction [3]. These models are capable of improving nonlinear mapping with the use of meteorological variables and past consumption data. However, independent machine learning models can be very demanding in terms of feature engineering and hyperparameter optimization, and such models may be impractical in rural areas with a small scale of computational resources. The recent advancements in deep learning constituted a significant contribution to the performance of short-term load forecasting. A hybrid CNN-LSTM based on attention mechanisms has been observed to have better skills in spatial correlations and temporal dependencies of power consumption data [4]. In the same vein, better CNN-BiLSTM models are more robust when applied to uncertain power system conditions because they are trained on two-way time association [5]. These structures are efficient in minimizing forecasting error as well as enhancing flexibility to varying agricultural load requirements. Forecasting predicts demand behaviour, whereas optimal scheduling provides efficient execution of demand-side control measures. Multi-objective genetic algorithm-based irrigation scheduling frameworks with real-time approaches have been suggested to ensure that there is a minimization of electricity cost and that water supply is sufficient [6]. Such strategies take into consideration the same time limitations, including the capacity of the pumps, the time of irrigation, and grid restrictions at the same time. Additional load profile management strategies that include water storage facilities also increase flexibility in agricultural areas since peak shift and load flattening can be applied [7]. These methods underscore the need to integrate physical infrastructure and smart optimization algorithms. Smart grids' load management models are based on demand-side load management, which focuses on grid efficiency and scheduling coordination [8]. Multi-objective methods of scheduling appliances build on this model by aiming to reduce the cost, peak demand, and user satisfaction at the same time [9]. The concept of tri-objective scheduling models in smart residential grids was proven to be feasible in terms of combining responsive loads with renewable energy sources and provided indications of the distributed energy optimization that can be applied to rural irrigation systems [10]. Metaheuristic optimization methods have gained interest in the solution of nonlinear multi-constraint energy management problems. Energy management strategies are based on the Optimization of the Grey Wolf and show high convergence properties in the case of a multi-objective load scheduling situation [11]. Hybrid GWO-PSO optimization methods also promote the balance of exploration and exploitation in high-dimensional energy dispatch optimization issues [12]. Such algorithms are especially appropriate in irrigation scheduling, where there are several conflicting goals to be optimized at the same time, with uncertainty. Although there has been great improvement in forecasting and optimization methods, most research undertakings consider the prediction and scheduling as separate processes. There are not many frameworks that combine advanced deep learning-based forecasting and real-time multi-objective irrigation scheduling with regard to rural infrastructure limitations. Moreover, the computational efficiency, uncertainty treatment, and scalable deployment are still unsolved. Thus, there is an imperative to have an integrated, flexible, computationally efficient forecasting scheduling model that has the capability to take in multidimensional environmental measurements, is responsive to grid dynamics, and can deliver water reliably with minimal cost of operation and peak demand pressure.

2 Literature Survey

Accurate short-term load forecasting (STLF) is of critical importance to the efficient operation of power systems, generation scheduling, and demand side management. With the growth in speed in the development of smart grid infrastructure and the penetration of renewable energy sources, some advanced forecasting and optimization techniques have been proposed to improve prediction accuracy and operation efficiency. Early research has been presented for metaheuristic types of optimization algorithms in the difficult scheduling and resource allocation issues for power systems. Techniques such as Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) have been used for best power dispatch, energy, and load scheduling. These algorithms demonstrated improved convergence and optimization functionality, which resulted in about 10%–18% better operational efficiency performance than conventional optimization methods [13–18]. Energy management in residential and distributed energy systems has also attracted much research attention. Studies have proposed the role of demand-side management (DSM) as well as the smart house energy management systems (HEMS) to schedule the operation of household appliances and electric vehicle charging operations. Multi-objective optimization algorithms enabled to minimize the electricity cost and peak load demand cost saving of ~12%–20% and peak load saving of nearly 15% in the smart grid environments [19–21]. With the availability of huge-scale smart meter data sets, machine learning and deep learning models have been extensively adopted for load forecasting applications. Advanced architectures and models such as sequence-to-sequence recurrent neural networks (Seq2Seq RNN) and attention-based models were proposed to model temporal dependencies in electricity demand data to enhance the accuracy of the forecast by around 8%–12% with respect to traditional regression methods [22]. Traditional statistical methods, such as Autoregressive Integrated Moving Average (ARIMA) models, are also largely adopted in this electricity demand prediction because of simplicity and interpretability. But these models are often unable to describe nonlinear load patterns. Hybrid models (ARIMA plus Artificial Neural Networks, ANN) have led to the mean absolute percentage error (MAPE) values of about 3% to 5% at the short-term load forecasting [23,24]. More recently, advanced deep learning architectures such as LSTM, CNN, and hybrid CNN-BiLSTM-Attention models have been published to have a superior performance than in the area of electricity demand prediction. These models manage to capture spatial and time dependence in load data and have been reported to have MAPE values as small as 1.8%–2.5% in the case of high-resolution forecasting tasks [25–35]. Despite such advancements, much developed research is based mainly on the prediction accuracy and doesn't integrate the forecasting in the balancing of the grid and scheduling the load optimally, which is considered an important challenge in the modern smart grid systems [36,37].

From the comparison presented in Table 1, it can be observed that in the recent research, the main purposes are to improve the accuracy of short-term load forecasting using statistical models, machine learning techniques, and newly developed deep learning architectures. The use of a hybrid CNN-BiLSTM-Attention model has shown high forecasting accuracy with MAPE values in the region of 2%–3%, which indicates how effective deep neural networks can be in learning spatial and temporal dependencies in electricity demand data. In comparison with these more advanced statistics techniques, the classical statistics methods (e.g., Auto-Regressive Integrated Moving Average [ARIMA]) are known for providing stable forecasting performance when they have to deal with linear data sets and relatively low computation requirements, but will struggle when dealing with nonlinear and highly variable patterns of loads. Artificial Neural Network (ANN) based models have better prediction capability and scheduling efficiency, which, on the other hand, have a drawback, i.e., careful tuning of parameters, and may be prone to overfitting for limited training data. Overall, these studies attest to the efficiency of advanced forecasting models but also to constraints in terms of the complexity of computations, dependency on data, and poor correlation with balancing mechanisms of the grid.

Table 1: Comparison of selected short-term load forecasting models based on methodology, forecasting performance, and limitations.

Citation	Technique/Model	Technical Methodology	Key Results	Limitations
[35]	Hybrid Deep learning load forecasting model	CEEMAN and Variational Mode Decomposition (VMD) CNN-BiLSTM-Attention based on high-resolution load forecasting. The spatial dimension feature extraction was based on CNN, and use of Bi-LSTM to use the temporal link, which is bi-directional.	Achieved MAPE 2.1%–2.4% of quarter-hourly load prediction, which is better than traditional neural network models in predicting the load.	Demands big data in terms of computational resources and data size of the training set because of the deep learning structure and signal decomposition phases.
[36]	Time-Series Forecasting Model in statistics.	Applies the Autoregressive Integrated Moving Average (ARIMA) model to describe the past and future of the electricity load within a historical setting based on the application of linear time-series modelling.	Delivers predictive stability in the form of MAPE of 4–5 with linear datasets that have low computing complexity.	Very inefficient when dealing with nonlinear and highly volatile load distribution, and thus it cannot be effectively used in the current smart grids.
[37]	ANN-Based Forecasting and Scheduling Model	Uses a multilayer Artificial Neural Network (ANN) in the modeling of nonlinear relationships in electricity demand and combines forecasting results with scheduling strategies for use in the power system.	Reduced scheduling efficiency and enhanced power system operation forecasting accuracy by over 90 percent.	ANN models require careful parameter tuning and may suffer from overfitting, especially with limited training data.

Though remarkable progress has been achieved in short-term load forecasting by all three approaches, namely the statistical, machine learning, and deep learning methods, there are still some challenges. The classical statistical model (ARIMA) has difficulties in modeling nonlinear and highly dynamic load patterns, and most machine learning and deep learning models have high demands regarding large training datasets and are computationally intensive. Also, the majority of the research out there is based on the actual processes of enhancing forecasting precision, and it does not pay sufficient attention to grid balancing and optimal load scheduling. Individually optimization methods like Particle Swarm Optimization (PSO) have been used to plan tasks, although they have rarely been combined with sophisticated forecasting systems. Consequently, it is necessary that an integrated approach be implemented that considers effective balancing of the grid that involves accurate load forecasting as a result of increasing reliability and energy efficiency of the power system.

The three objectives of this work are clearly spelled out.

1. The former is to create a precise load forecasting model, which has the potential to predict the short-term power demand and address the seasonal variation and fluctuations.
2. The second is to balance the grid, the predicted load, and the available grid capacity to have a stable and reliable grid.
3. The third goal is to develop a useful approach to loading that will distribute the electrical loads to the appropriate time frames, hence contributing to a decrease in the peak load and enhancing the exposure of the energy.

3 Proposed Methodology

The suggested Agricultural Load Forecasting and Scheduling (ALFS) model is an integration of deep learning and optimization to enhance the control of irrigation energy usage in rural farming systems. This methodology starts with the pre-processing of the agriculture and environmental inputs, which include temperature, rainfall, humidity, soil moisture, crop growth stage, and historical pump-load data. These are the variables extracted as the result of the JVVNL agricultural electricity consumption data of twelve districts in Rajasthan, which are being cleaned and normalized by Min-max scaling and transformed into supervised time-series sequences by a sliding-window method. A hybrid CNN–BiLSTM model is then employed for short-term load forecasting. The CNN extracts local spatial–temporal patterns, while the Bi-LSTM captures long-range bidirectional dependencies. The network is trained using the Adam optimizer and MSE loss to ensure stable and accurate predictions. The forecasted load is evaluated by a Grid Balancing Module, which checks transformer limits and peak-hour constraints to prevent voltage instability common in rural feeders. Based on the validated forecast, a Particle Swarm Optimization (PSO) algorithm generates an optimal irrigation schedule by minimizing energy cost, avoiding transformer overload, and meeting water demand requirements. Finally, a real-time feedback loop compares actual and predicted loads and adaptively updates the forecasting and scheduling parameters, ensuring reliable, efficient, and grid-friendly agricultural energy usage. The overview of the proposed system is diagrammatically shown in Fig. 1 with a detailed explanation of the following process.

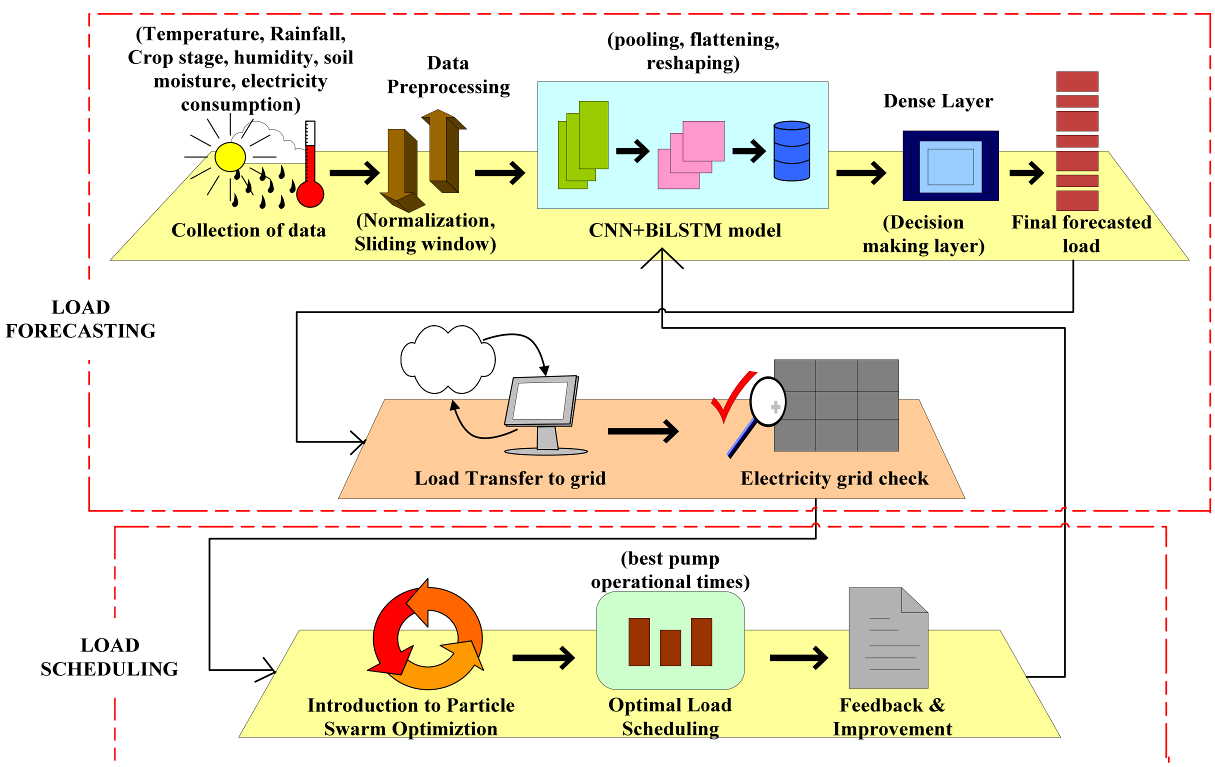


Figure 1: Block diagram of the proposed system.

3.1 Load Forecasting

The predictive step of the whole scheme of power management is the load forecasting. It starts with a systematic buying of a compilation of data sets that affect the use of agricultural energy, such as the weather conditions like temperature, humidity, rainfall, and the wind speed, the water condition of the soil, the developmental stage of the crop, and the previous history of electrical utilization. The next step after the data collection is to intensively preprocess the data to guarantee the quality and consistency of the data. It involves the process of addressing missing values, noise, outliers, Min-Max scaling, characteristic normalization, and the production of sliding-window sequences to preserve the time sequence. A CNN-k

BiLSTM model is input with the filtered data. The convolutional layers are also trained on short-term variations, the Bi-LSTM layers on long-term variations, which means that there are multi-day agricultural behaviors and a seasonal load. The model is also trained using gradient-based training also known as the Adam optimizer to reduce prediction error. The outcome of this action is to be able to predict the future load demand with high precision, and it is on this basis that all the grid balancing and scheduling actions are performed based on prediction.

The forecasting model shown in Fig. 2 follows a fully connected flow beginning with a 24-step time-series input, which is first passed through a 1D Convolution layer that extracts short-term temporal patterns using 256 filters and a kernel size of 3. The feature map generated by this convolution is regularized through a dropout layer (0.1) to prevent overfitting before being fed into two stacked Bidirectional LSTM layers.

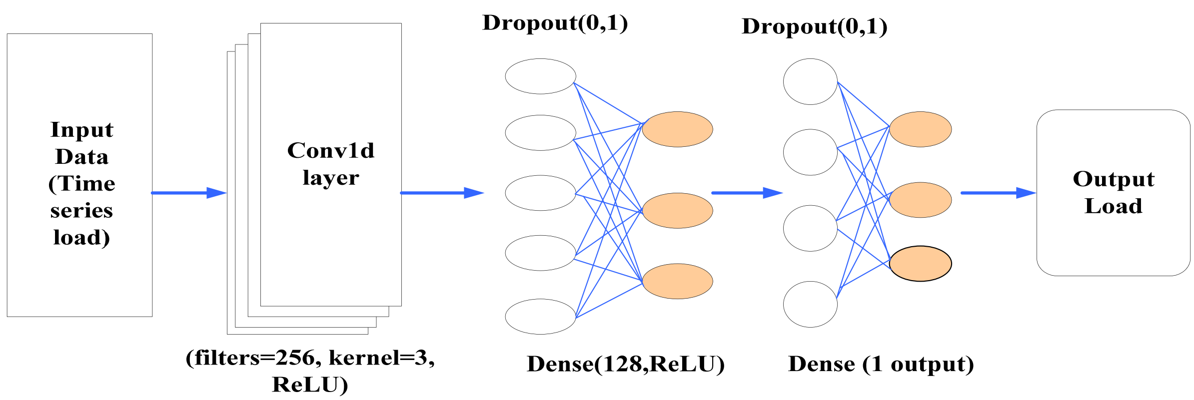


Figure 2: Convolutional neural network (CNN) architecture.

The sequence of units in the first Bi-LSTM block performs processing on the sequence in both forward and backward directions of 512 units, so that the model may learn long-range dependencies and long-range interactions occurring over time. This layer produces the output that is supplied to the second block of BiLSTMs with 256 units, whereby the more profound temporal patterns are mirrored, and the seasonal fluctuations are encoded.

The final temporal representation produced by the BiLSTMs is then connected to a Dense layer with 128 neurons activated by ReLU to learn non-linear relationships in the load behaviour. Another dropout layer (0.1) further stabilizes learning as shown in Fig. 3. The processed features then flow into the final output layer, a single-neuron Dense unit, which produces the next forecasted load (kW). This connected architecture ensures smooth information flow from short-term convolutional feature extraction to long-term bidirectional sequence learning, ultimately enabling accurate agricultural load prediction.

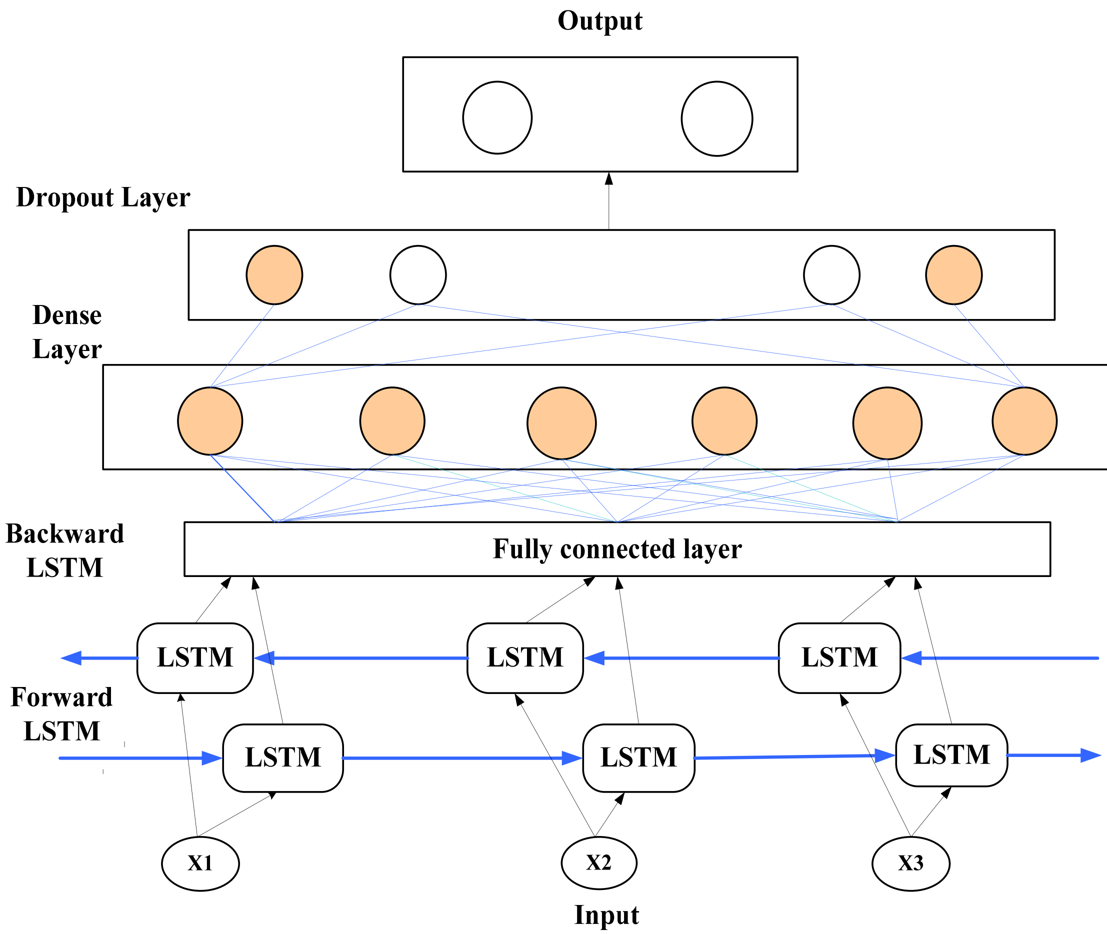


Figure 3: Bidirectional long-short term memory (BiLSTM) architecture.

3.2 Grid Balancing

The step of grid balancing will either decide the ability or inability of the forecasted irrigation load to be safely within the operating limits of the electrical distribution system. The forecasted load is checked against the maximum capacity of the grid and other system limitations to make sure that the network is operating in a safe range. When the forecasted demand falls within the acceptable limit, the system will go about with normal scheduling. But in the case where the projected load is higher than the grid capacity, the load is shifted to other time periods. This is through breaking massive loads into small parts and timing them in the best way to ensure that the magnitude of the load at any given time does not exceed the capacity of the grid, and stable and consistent grid running. The above grid capacity checking process is shown in Fig. 4.

3.3 Load Scheduling

Particle Swarm Optimization (PSO) is the load scheduling step that is undertaken to schedule the predicted loads of agriculture within the grid capacity. The forecast demand of a particular crop is then divided into small parts whenever the load in any single grid exceeds the maximum grid capacity, and in the second step, the dynamic operating length of each piece is determined as the ratio of chunk load over grid capacity. As shown in Fig. 5, a PSO algorithm on global best is then applied, in which all particles are the candidate schedules that include the start time of all load chunks within 24 horizons. The optimization is performed on the 50 particles in 200 steps with acceleration coefficients, $c1 = 0.5$, $c2 = 0.3$, and inertia weight $w = 0.9$. The scheduling algorithm restricts the possible start time for each load chunk within a specific range.

The search space (possible scheduling time) is limited between 0 and 24 h, which represents the 24-h daily scheduling period. This means the optimizer can choose any start time within this 24-h window to schedule each load chunk. The fitness function discourages any act of violation of the grid capacity as the total of overloads is minimized by time (time intervals of 0.1 h). The answer to this is the compilation of chunk schedules of separate crops to arrive at continuous start and finish times to ensure that transformer and feeder boundaries are met, and a uniform load balance and constant system operation is obtained.

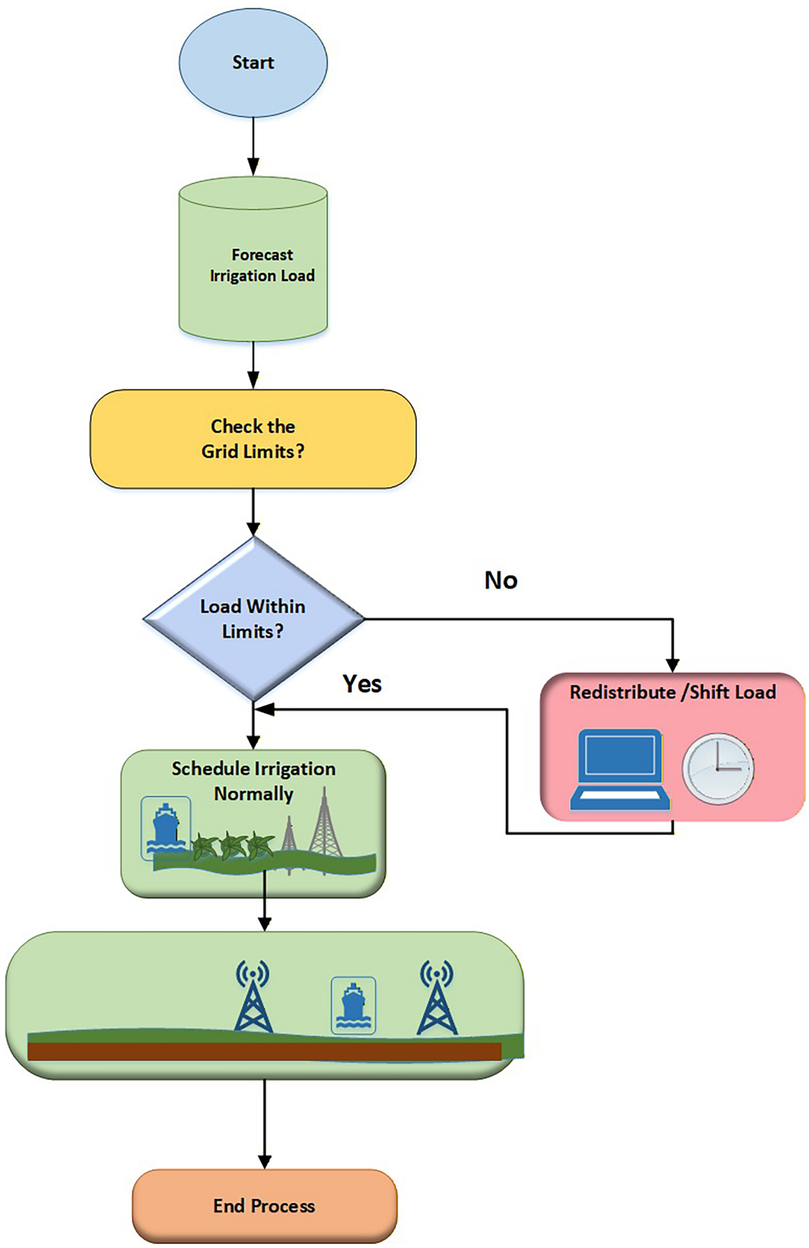


Figure 4: Flowchart of the proposed irrigation load forecasting and grid limit checking process.

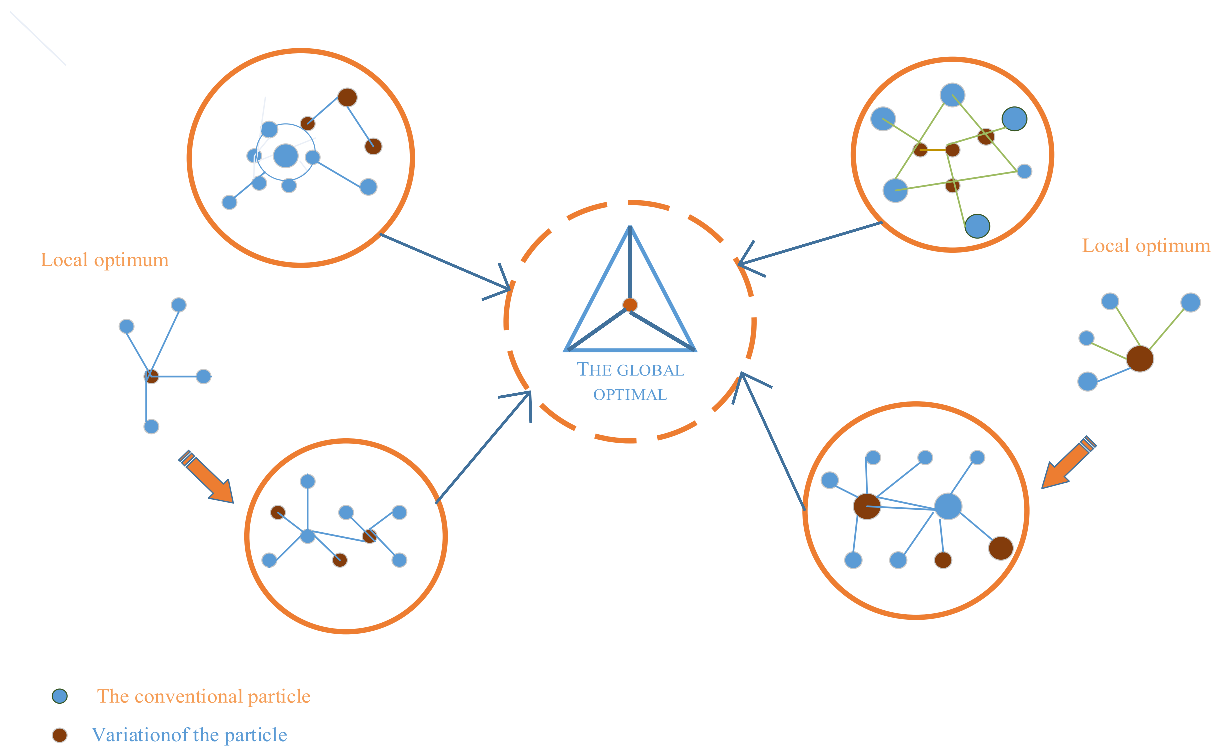


Figure 5: PSO illustration displaying the search on local optima and eventual convergence to the local optima.

4 Mathematical Modelling of the Proposed Methodology

The agricultural power requirement used in the paper will have great nonlinear, time-varying, and weather-dependent crop-dependent properties. The consumption of agriculture in comparison with domestic or industrial loads is very irregular because of the intermittent irrigation patterns, switching of pumps, seasonal demand peaks, decline of crops, and impulsive switching of motors on and off. The factors bring about sudden fluctuations and time dependency, which cannot be well represented by classical linear or statistical forecasting. Thus, a hybrid mathematical modelling framework that would offer simultaneous solutions to the accurate prediction of loads and the optimal scheduling of loads is needed. Fig. 6 explains the workflow in the proposed system.

4.1 CNN-Bi-LSTM Equations

The CNN-Bi-LSTM-based forecasting framework suggested in this work is specially made to cope with the nonlinear, fluctuating, and crop-dependent features of agricultural electrical loads. Agricultural loads tend to have sudden pump operations, erratic irrigation cycles, and crop-based variations that are flabbergasting linear forecasting methods. Therefore, a hybrid deep learning model that has the advantage of picking up local short-term changes and at the same time capturing long-term temporal dependencies is essential. The combined use of convolutional neural networks (CNN's) with bidirectional long short-term memory networks (BiLSTM) is a good way to address these issues, by integrating both the extraction of patterns in local regions, combined with learning in a deep time sequence.

The working principles and inducements behind every layer are mentioned below. The input into the model is a sequence of the preceding 24 load observations given by Eq. (1):

$$Xt = [Lt - 23, \ldots, Lt] \tag{1}$$

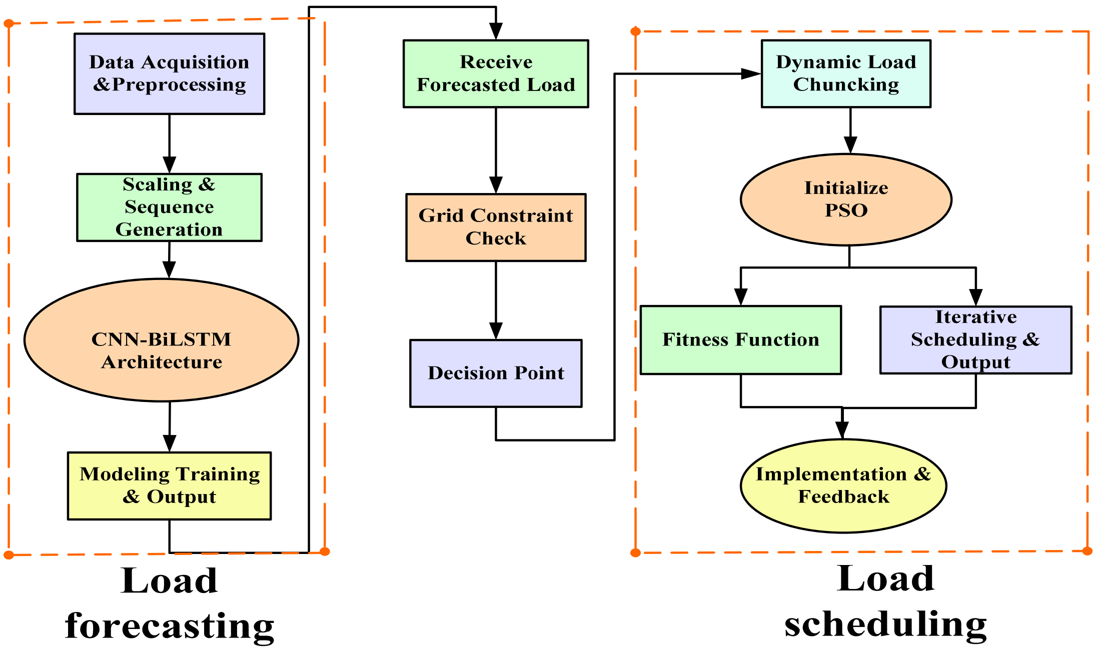


Figure 6: Flowchart explaining the process in the proposed system.

This time window is chosen in order to capture an entire daily cycle of agricultural activity, an aspect that is very important to modelling load patterns associated with irrigation. The first part of the model is a one-dimensional convolutional layer. Agricultural load data often includes short-duration spikes from pumps switching, motor start-up surges, and fast changes in water use. These abrupt variations are not easy to/detect for recurrent networks only. Hence, there is a need for CNN layers so as to extract the local temporal features before providing the data to the deeper layers. The convolutional operation is given as and in Eq. (2):

$$F(t) = \sigma(W * Xt + b) \tag{2}$$

here, W and b are the parameters in the kernel function, and then, is the ReLU activation function. By learning and storing short-term dependencies, the CNN helps to stabilize the learning process, thus ensuring that the small-scale fluctuations are well represented. After local feature extraction using CNN features, all these features are sent to the Bi-LSTM layer. Unidirectional LSTM can only detect past-to-future relationships and deals with the sequence in two directions, providing a more holistic temporal relationship. For the forward LSTM, the gating mechanisms are given by Eqs. (3)–(5):

$$t = \delta(Wf[ht-1, F(t)] + bf) \tag{3}$$

$$it = \delta(Wi[ht-1, F(t)] + bi) \tag{4}$$

$$C \sim t = \tanh(Wc[ht-1, F(t)] + bc) \tag{5}$$

The memory updates follow Eq. (6):

$$Ct = ft \odot Ct-1 + it \odot C \sim t, ht = ot \odot \tanh(Ct) \tag{6}$$

The backward process of LSTM is to run backwards in the sequence given by Eq. (7):

$$ht = LSTM(F(1), \ldots, F(t), \backslash cevht = LSTM(F(T), \ldots, F(t)) \tag{7}$$

The concatenation of them produces the final output of the Bi-LSTM given by Eq. (8):

$$htBi = [ht, \backslash cevht] \tag{8}$$

The reason to make use of a Bi-LSTM is the fact that agricultural load behaviour is influenced by past and future events within a daily cycle. For instance, irrigation operations practiced in the morning might be a function of moisture conditions influenced by nighttime watering, whereas evening loads might be representative of the use of earlier in the day pumps. By modeling these two-way relationships, the Bi-LSTM enables a complete comprehension of the time, which is needed in order to make an accurate prediction of a situation. The resultant combined temporal features are further fed to a deeply connected dense layer, which helps in fine-tuning and consolidating the learning. This transformation is given in Eq. (9).

$$a = \sigma\left(WdhtBi + bd\right) \tag{9}$$

The dense layer is needed to isolate the most relevant patterns that are obtained from the recurrent layers, and in order to filter out the irrelevant fluctuations in order to ensure that only the most significant temporal cues contribute to the final prediction. Then, the predicted load value is generated in the output layer using a linear transformation that follows Eq. (10):

$$L^{t} + 1 = Woa + bo \tag{10}$$

The prediction is then inverse normalized to give the actual load prediction in kilowatts. The model is trained based on Mean Squared Error (MSE), which is defined as in Eq. (11)

$$J = N1i = 1 \sum N \left(Li - L^{i}\right) 2 \tag{11}$$

which penalizes the deviations between the predicted values and actual values and ensures smooth and reliable forecasting outputs. Overall, the CNN-Bi-LSTM architecture plays an important role as it combines both the short-term feature extraction and long-term temporal learning functionality requirements, which enables the model to accurately capture the complex and irregular patterns in agricultural load data. The resultant dependable predictions help in the efficient assignment of loads while assuring that the grid capacity constraints are always met.

4.2 PSO Scheduling Equations

In the proposed system, the agricultural loads like irrigation motors, processing machines, and pumping units are considered as dynamic electrical loads whose power consumption depends on the crop type and their working condition. Since these loads can never exceed maximum allowable grid capacity, the load scheduling model includes various physical and operational constraints for load scheduling to ensure safe and stable operation of the system.

Because some crop loads may violate the grid's maximum permissible load at a given time, the major forecasted load of each crop is broken into several sub-loads known as chunks. This chunking mechanism eliminates each segment, keeps it at the permissible operational range, and nonetheless retains the general necessary energy for every crop. Each chunk is then given a dynamic operating time proportional to its power rating. PSO optimizes the timings at which these chunks are started so as to minimize or totally avoid grid overload.

Although agricultural scheduling does not include distributed generation units, the basic goal is also similar: the sum of the instantaneous load must not exceed the maximum grid capacity. Accordingly, at any time t, the scheduled load must comply with Eq. (12):

$$Ptotal\left(t\right) \leq Pgrid, max \tag{12}$$

here, *Ptotal*(t) represents the total of all crop loads that are being scheduled to operate at time t. *Pgrid, max* is the maximum number of kW allowed on the grid (e.g., 4000 kW in this study). This constraint is to ensure that the rural distribution transformer and feeder lines are safe from thermal overloading, voltage fluctuations, and system instability. For a crop which predicted load L if: $L > Pgrid, max$, the load has to be cut into n smaller pieces, shown in Eq. (13):

$$n = \left[Pgrid, maxL\right] \tag{13}$$

The amount of load assigned to each chunk follows Eq. (14);

$$Lc = nL \tag{14}$$

And its corresponding time of operation in the scheduling horizon is given by Eq. (15):

$$Tc = Pgrid, maxLc \tag{15}$$

This constraint means that no individual chunk can exceed the allowable power limit, and at the same time, it maintains the energy required by the crop. It also helps to schedule fine-grained and it decreases system stress. Bearing this in mind, each chunk must be scheduled within the 24-h operational window as shown in Eq. (16):

$$0 \leq sj \leq \left(24 - Tj\right) \tag{16}$$

where *sj* is the scheduled start time of chunk *j*, *Tj* is the duration for which it should be operated. This constraint restrains the scheduling algorithm from having load segments allocated outside the daily window.

To make sure that the overloads are penalized when optimizing, PSO uses the following fitness function given by Eq. (17):

$$Fitness = t \sum max\left(0, Ptotal\left(t\right) - Pgrid, max\right) \tag{17}$$

This function only imposed a penalty when the total load was above the grid limit and thus helped the PSO algorithm approach feasible schedules by preventing any overloads. When the PSO algorithm is implemented for optimal scheduling for agricultural loads, the process starts by initializing the particles with the help of predicted load profiles made using a CNN-BiLSTM load forecasting model.

Each particle is a potential schedule, with all randomly generated initial velocities and positions, and corresponding different starting times for the sample load chunk. At each iteration, an update of the positions and velocities of particles according to the classical PSO equations is used: Velocity Update given by Eq. (18):

$$vik + 1 = wvik + c1r1\left(pbesti - xik\right) + c2r2\left(gbest - xik\right) \tag{18}$$

Position Update given by Eq. (19):

$$xik + 1 = xik + vik + 1 \tag{19}$$

here, w is the inertia weight used to balance the exploration and exploitation, $c1$ and $c2$ are the cognitive and social coefficients. $r1$, $r2$ are the random values in [0, 1]. Here, pbesti is the best solution found by particle I, and gbest is the global best solution found by the swarm. Through this iterative update mechanism shown in Fig. 7, particles gradually converge to one that minimizes overloading.

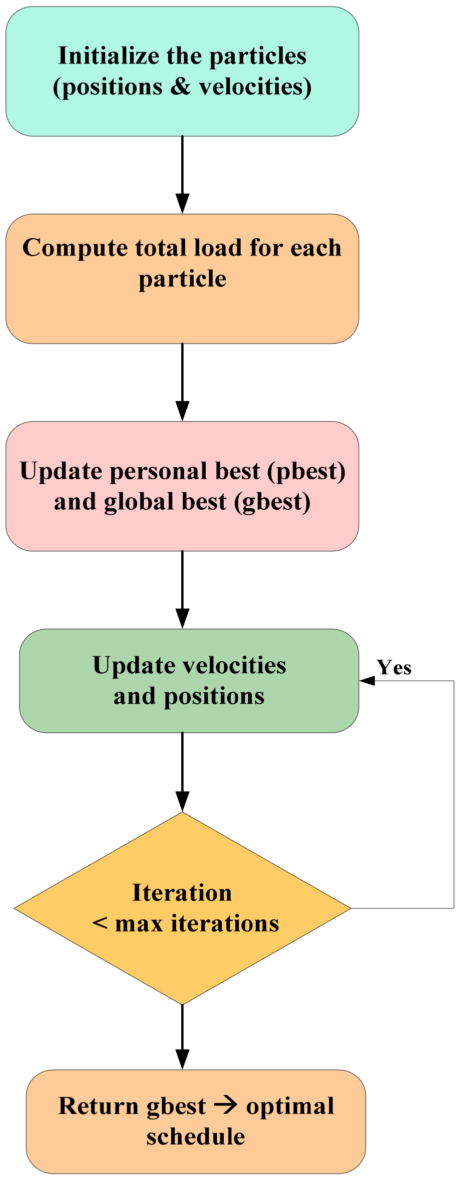


Figure 7: Iterative update mechanism in PSO.

5 Results

For this study, the electricity consumption dataset from JVVNL (Jaipur Discom) is utilized, which contains actual and average electricity usage data collected from consumers across 12 districts of Rajasthan, i.e., Alwar, Baran, Bundi, Bharatpur, Dausa, Dholpur, Jaipur, Jhalawar, Karauli, Kota, Sawaimadhopur, and Tonk. Based on climatic conditions, these districts are categorized into three zones as seen in Table 2.

Table 2: Classification of selected Rajasthan agro-climatic zones with districts.

Zone	Agro-Climatic Type	Districts Included
Zone 1	Semi-arid eastern plain	Jaipur, Alwar, Dausa, Tonk
Zone 2	Flood-prone eastern plain	Bharatpur, Dholpur, Karauli
Zone 3	Humid south-eastern plain	Sawaimadhopur, Jhalawar, Bundi, Kota, Baran

The original dataset contained a variety of columns, but for load forecasting and scheduling, only relevant columns were retained. The dataset contains four main crops (wheat, maize, sugarcane, rice), each with time-series observations of electrical load and environmental variables.

Table 3 shows a section of the dataset containing columns of agricultural load demand and other environmental parameters recorded for the maize crop for every irrigation cycle. The model is trained for each crop, which means a separate model is developed for processing each crop's agricultural load demand and environmental parameters.

Table 3: A section of the dataset having the agricultural load demand and environmental parameters for the crop Maize.

Date	Agricultural Load Demand (kW)	Temperature (°C)	Humidity (%)	Rainfall (mm)	Soil Moisture (%)	Solar Irradiance (W/m^2)	Crop Type
2023-01-01	141	31.9	59.7	20	21.3	283	Maize
2023-01-08	86	38.1	67.5	2	63.5	967	Maize
2023-01-13	171	23.3	55.6	0	30.4	321	Maize
2023-01-14	178	22.1	58.6	0	48.6	401	Maize
2023-01-17	93	36.7	59.8	20	27.5	55	Maize
2023-01-23	246	33.4	63.3	0	26.9	248	Maize

To ensure reproducibility and assess the stability of the proposed system, experiments were conducted using five different random seeds: 42, 52, 62, 72, and 82 for each crop. For each run, the corresponding seed was set for NumPy and TensorFlow to control stochastic variations during model training. As seen in Fig. 8, the experiments were conducted using Python Version 3.12.13 with TensorFlow 2.20.0. The model training was performed in a GPU-enabled environment, although CPU execution is also supported.

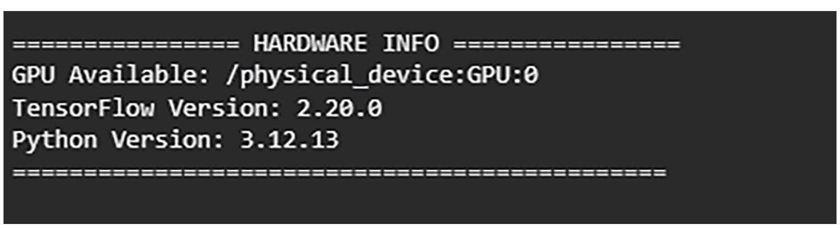


Figure 8: Hardware and software environment used for model training.

5.1 Load Forecasting and Scheduling

A CNN-BiLSTM architecture of Tensorflow-Keras was used to implement the load forecasting model to recognize non-liberal temporal relationships in crop-wise agricultural load demand records. The input to the model is a multi variate time-series that also uses a lookback size of 24-time steps resulting in a sized input of (24, 6 + k). The feature extraction of time is carried out by a Conv1D filter of 256 filters and a size of the kernel of 3 with a dropout layer (0.1) at the end to regularize it. The resulting features are fed to two stacked Bidirectional LSTM layers which have 512 and 256 units respectively and by doing so the model can learn the forward as well as the backward temporal relationship. The learned representation is again trained with a dense layer containing 128 neurons (ReLU activation) and one more dropout layer, followed by a one-neuron, output, load prediction layer. This architecture has 1,744,897 parameters to be trained, and it is trained with Adam optimizer (learning rate = 0.00015) and mean squared error (MSE) loss. The dataset yields samples of wheat, rice, maize and sugarcane as observed using a sliding window method with a lookback length of 24 that were divided using a strictly chronological temporal split into an 80 percent training and 20 percent testing sample. The model was trained with a batch size of 8 until 400 epochs and this equates to about 1650–1750 iterations per epoch. The Early Stopping (patience = 20) and ReduceLROnPlateau were used to increase the training stability, and to smooth the input data, the rolling filters and Min-Max scaling were implemented ahead of the training. The pipeline performed temporal sorting, resampling to a uniform 1-h interval, mean aggregation for numerical variables, forward filling for categorical variables and time-based interpolation for missing intermediate values for categorical variables. Rolling mean and rolling median smoothing were applied separately to the training and testing partitions Missing values were handled using time-based interpolation and residual missing-value imputation. Outliers were treated quantitatively using the Interquartile Range (IQR) method computed only from the training set. All hyperparameters, preprocessing steps, and module dependencies are explicitly defined as the same for each crop as seen in Fig. 9.

```
==================================================
Model Summary for Rice
==================================================

Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 24, 256)	4,864
dropout (Dropout)	(None, 24, 256)	0
bidirectional (Bidirectional)	(None, 24, 512)	1,050,624
bidirectional_1 (Bidirectional)	(None, 256)	656,384
dense (Dense)	(None, 128)	32,896
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

```
 Total params: 1,744,897 (6.66 MB)
 Trainable params: 1,744,897 (6.66 MB)
 Non-trainable params: 0 (0.00 B)

Total Trainable Parameters: 1744897
```

Figure 9: Summary of the CNN-BiLSTM sequential model architecture defined as the same for each crop.

Case 1-Maize Crop

The CNN-BiLSTM model was tested five times for the case of the rice crop with random seeds 42, 52, 62, 72 and 82. The model took an average of 2168.35 s to train and was converged in an average of 76.6 epochs. The average forecasted rice load demand for the subsequent forecasting period was 216.85 kW as seen in Fig. 10.

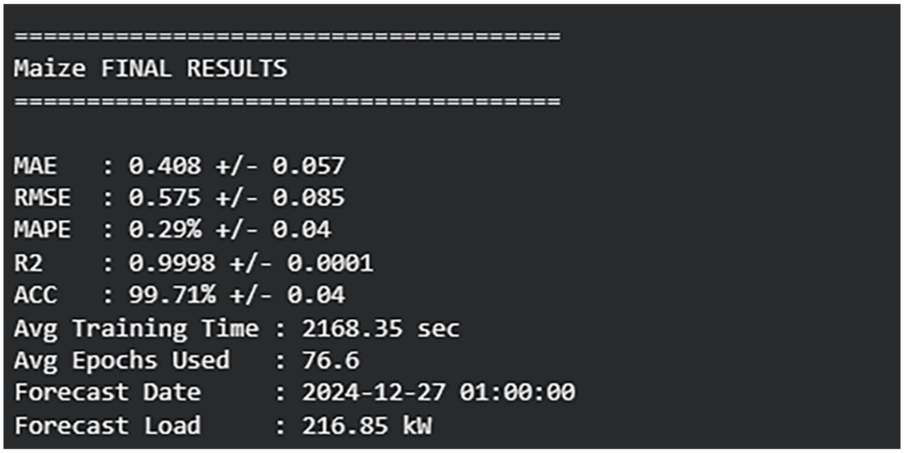


Figure 10: Training results and evaluation metrics for the Maize crop.

The seed-wise forecasting performance of the CNN-BiLSTM model is shown in the Table 4, for the maize crop.

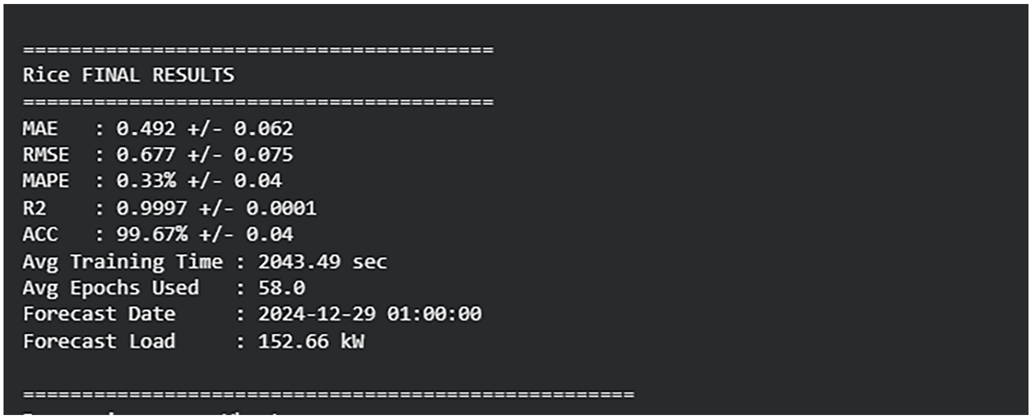
Table 4: Record of the evaluation metrics of maize crop for 5 different seeds.

Crop	Seed	MAE	RMSE	MAPE (%)	R^2	Training Time (s)	Epochs Used	Forecasted Load (kW)
Maize	42	0.381	0.541	0.27	0.9998	1845.63	68	216.12
Maize	52	0.392	0.553	0.28	0.9998	1938.74	72	216.58
Maize	62	0.417	0.587	0.30	0.9997	2245.91	79	217.31
Maize	72	0.436	0.612	0.31	0.9997	2418.57	82	216.74
Maize	82	0.414	0.584	0.29	0.9997	2392.88	82	217.52

Considering all five random-seed runs, the maize crop achieved an average MAE of 0.408 ± 0.057 kW, RMSE of 0.575 ± 0.085 kW, and MAPE of 0.29 ± 0.04%. The mean R^2 score was 0.9998 ± 0.0001, while the average MAPE-derived forecasting accuracy was 99.71 ± 0.04%.

Case 2-Rice Crsop

The CNN-BiLSTM model was tested five times for the case of the rice crop with random seeds 42, 52, 62, 72 and 82. The model took an average of 2043.49 s to train and was converged in an average of 58.0 epochs. The average forecasted rice load demand for the subsequent forecasting period was 152.66 kW as seen in Fig. 11.



```
========================================
Rice FINAL RESULTS
========================================
MAE   : 0.492 +/- 0.062
RMSE  : 0.677 +/- 0.075
MAPE  : 0.33% +/- 0.04
R2    : 0.9997 +/- 0.0001
ACC   : 99.67% +/- 0.04
Avg Training Time : 2043.49 sec
Avg Epochs Used   : 58.0
Forecast Date     : 2024-12-29 01:00:00
Forecast Load     : 152.66 kW

====================================================
```

Figure 11: Training results and evaluation metrics for the rice crop.

The seed-wise forecasting performance of the CNN-BiLSTM model is shown in the Table 5, for the rice crop.

Table 5: Record of the evaluation metrics of rice crop for 5 different seeds.

Crop Name	Seed	MAE	RMSE	MAPE (%)	R^2	Training Time (s)	Epochs Used	Forecasted Load (kW)
Rice	42	0.470	0.638	0.31	0.9997	1694.63	48	152.32
Rice	52	0.429	0.601	0.29	0.9997	2115.06	60	152.69
Rice	62	0.500	0.687	0.33	0.9997	1245.61	39	153.18
Rice	72	0.594	0.798	0.39	0.9995	2134.45	64	151.92
Rice	82	0.467	0.660	0.32	0.9997	3027.71	79	153.19

The final results show that the model achieved a mean MAE of 0.492 ± 0.062 kW and an RMSE of 0.677 ± 0.075 kW. The repeated runs had a very small relative forecasting error of 0.33 ± 0.04% (mean and standard deviation of the MAPE). The model achieved high R^2 value of 0.9997 ± 0.0001 showing a high degree of agreement between the predicted and actual load demand of rice crop. On the whole the seed-wise results suggest that the model is robust and repeatable with minor changes in forecasting error and in the values of the next load in the time series, when the model is run over and over.

Case 3-Sugarcane Crop

The CNN-BiLSTM model was tested five times for the case of the rice crop with random seeds 42, 52, 62, 72 and 82. The model took an average of 2296.52 s to train and was converged in an average of 82.6 epochs. The average forecasted rice load demand for the subsequent forecasting period was 82.14 kW as seen in Fig. 12.

The seed-wise forecasting performance of the CNN-BiLSTM model is shown in the Table 6, for the sugarcane crop.

```
======================================
Sugarcane FINAL RESULTS
======================================

MAE   : 0.471 +/- 0.073
RMSE  : 0.664 +/- 0.106
MAPE  : 0.34% +/- 0.06
R2    : 0.9996 +/- 0.0001
ACC   : 99.66% +/- 0.06
Avg Training Time : 2296.52 sec
Avg Epochs Used   : 82.6
Forecast Date     : 2024-12-31 01:00:00
Forecast Load     : 82.14 kW
```

Figure 12: Training results and evaluation metrics for the sugarcane crop.

Table 6: Record of the evaluation metrics of sugarcane crop for 5 different seeds.

Crop	Seed	MAE	RMSE	MAPE (%)	R^2	Training Time (s)	Epochs Used	Forecasted Load (kW)
Sugarcane	42	0.432	0.608	0.31	0.9997	2015.34	74	81.62
Sugarcane	52	0.458	0.644	0.33	0.9996	2386.47	83	82.05
Sugarcane	62	0.489	0.689	0.35	0.9996	2491.63	85	82.54
Sugarcane	72	0.521	0.731	0.38	0.9995	2614.26	88	81.93
Sugarcane	82	0.455	0.648	0.33	0.9996	1975.42	83	82.56

Considering all five random-seed runs, the sugarcane crop achieved an average MAE of 0.471 ± 0.073 kW, RMSE of 0.664 ± 0.106 kW, and MAPE of 0.34 ± 0.06%. The mean R^2 score was 0.9996 ± 0.0001, while the average MAPE-derived forecasting accuracy was 99.66 ± 0.06%.

Case 4-Wheat Crop

The CNN-BiLSTM model was tested five times for the case of the rice crop with random seeds 42, 52, 62, 72 and 82. The model took an average of 2148.35 s to train and was converged in an average of 75.8 epochs. The average forecasted rice load demand for the subsequent forecasting period was 104.83 kW as seen in Fig. 13.

```
======================================
Wheat FINAL RESULTS
======================================

MAE   : 0.389 +/- 0.052
RMSE  : 0.553 +/- 0.078
MAPE  : 0.26% +/- 0.03
R2    : 0.9998 +/- 0.0001
ACC   : 99.74% +/- 0.03
Avg Training Time : 2148.35 sec
Avg Epochs Used   : 75.8
Forecast Date     : 2024-12-30 01:00:00
Forecast Load     : 104.83 kW
```

Figure 13: Training results and evaluation metrics for the wheat crop.

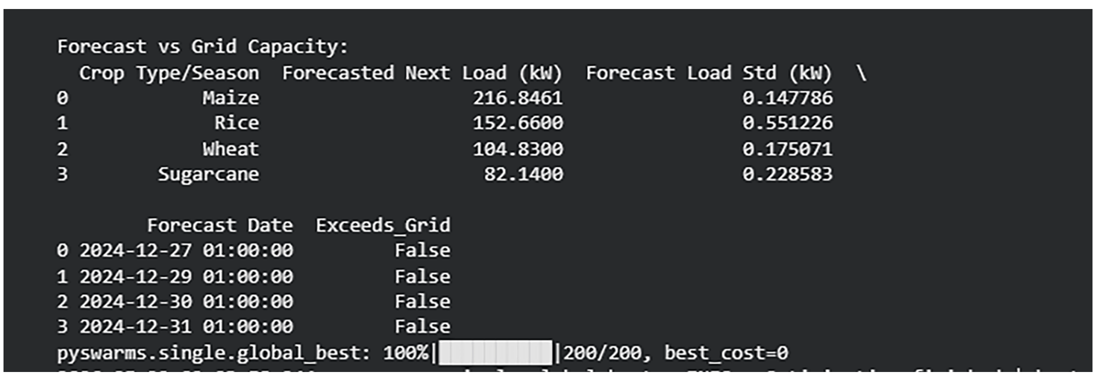
The seed-wise forecasting performance of the CNN-BiLSTM model is shown in the Table 7, for the wheat crop.

Table 7: Record of the evaluation metrics of wheat crop for 5 different seeds.

Crop	Seed	MAE	RMSE	MAPE (%)	R^2	Training Time (s)	Epochs Used	Forecasted Load (kW)
Wheat	42	0.352	0.502	0.24	0.9998	1948.27	69	104.26
Wheat	52	0.371	0.534	0.25	0.9998	1865.94	71	104.61
Wheat	62	0.421	0.589	0.28	0.9997	2284.46	82	105.18
Wheat	72	0.398	0.557	0.27	0.9998	2195.37	79	104.82
Wheat	82	0.403	0.584	0.27	0.9998	2447.71	78	105.27

Considering all five random-seed runs, the wheat crop achieved an average MAE of 0.389 ± 0.052 kW, RMSE of 0.553 ± 0.078 kW, and MAPE of 0.26 ± 0.03%. The mean R^2 score was 0.9998 ± 0.0001, while the average MAPE-derived forecasting accuracy was 99.74 ± 0.03%.

As seen in Fig. 14, the computed irrigation load of each crop was contrasted with the grid capacity supply to check system feasibility. The outcomes show that the projected loads of maize, rice, sugarcane, and wheat are within the restricts of the grid capacity since they have not plotted any of their forecasted value to exceed the maximum capacity.



```
Forecast vs Grid Capacity:
  Crop Type/Season  Forecasted Next Load (kW)  Forecast Load Std (kW)  \
0            Maize                   216.8461                0.147786
1             Rice                   152.6600                0.551226
2            Wheat                   104.8300                0.175071
3        Sugarcane                    82.1400                0.228583

        Forecast Date  Exceeds_Grid
0 2024-12-27 01:00:00         False
1 2024-12-29 01:00:00         False
2 2024-12-30 01:00:00         False
3 2024-12-31 01:00:00         False
pyswarms.single.global_best: 100%|██████████|200/200, best_cost=0
```

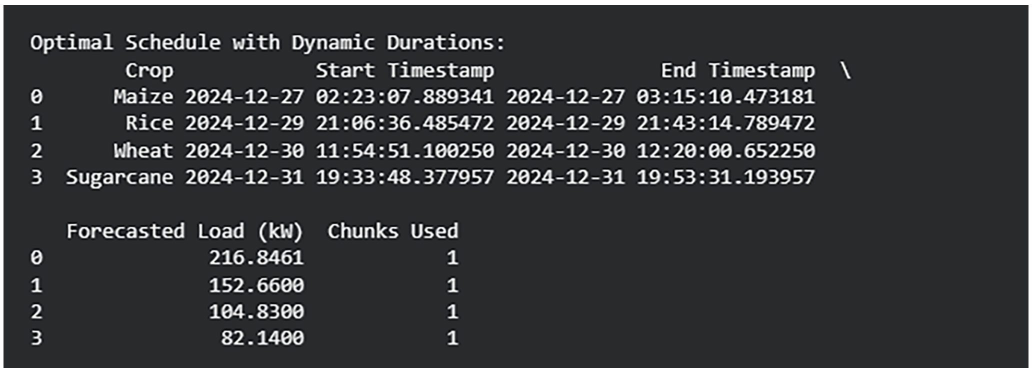
Figure 14: Training results showing forecasted crop loads compared with grid capacity.

The predicted loads crop based were then converted as inputs into the PSO based load scheduling model and ultimately the results of the schedule are combined in Table 8.

As seen in Fig. 15, the schedule is within grid capacity, and it proved that the suggested scheduling method was effective when dealing with peak loads and the ability to deliver power with high reliability.

Table 8: Crop-wise load scheduling results (PSO-based).

Crop Type	Scheduled Load (kW)	Schedule Date	Start Time	End Time	Grid Capacity (kW)	Grid Constraint Status
Maize	216.84	27-12-2024	02:23:07	03:15:10	250	Satisfied
Rice	152.66	29-12-2024	21:06:36	21:43:14	250	Satisfied
Sugarcane	104.83	31-12-2024	11:54:51	12:20:00	250	Satisfied
Wheat	82.14	30-12-2024	19:33:48	19:53:31	250	Satisfied



```
Optimal Schedule with Dynamic Durations:
        Crop           Start Timestamp              End Timestamp  \
0      Maize 2024-12-27 02:23:07.889341 2024-12-27 03:15:10.473181
1       Rice 2024-12-29 21:06:36.485472 2024-12-29 21:43:14.789472
2      Wheat 2024-12-30 11:54:51.100250 2024-12-30 12:20:00.652250
3  Sugarcane 2024-12-31 19:33:48.377957 2024-12-31 19:53:31.193957

   Forecasted Load (kW)  Chunks Used
0              216.8461            1
1              152.6600            1
2              104.8300            1
3               82.1400            1
```

Figure 15: Optimal load scheduling results for each crop showing the start time, end time and the corresponding load demand.

5.2 Crop-Wise Forecasting Performance of Load

Leveraging the acquired dataset, the demand of the electric load of each crop was estimated with the help of the created CNN-BiLSTM model. Quantitative assessment of the forecasting performance was done as indicated in Table 9 by using some of the most popular statistical error measures that both assess accuracy and strength of the proposed model. A shown in Table 9, the metrics used in forecasting the performance configuration are MAE, RMSE, MAPE, R^2, and the graphical analysis should support the obtained numerical values in order to give a complete understanding of model reliability.

Table 9: Forecasting performance of the CNN-BiLSTM model for each crop.

Crop Type	MAE (kW)	RMSE (kW)	MAPE (%)	R^2	Forecast Accuracy (%)
Maize	0.408 ± 0.057	0.575 ± 0.085	0.29% ± 0.04	0.9998 ± 0.0001	99.71% ± 0.04
Rice	0.492 ± 0.062	0.677 ± 0.075	0.33% ± 0.04	0.9997 ± 0.0001	99.67% ± 0.04
Sugarcane	0.471 ± 0.073	0.664 ± 0.106	0.34% ± 0.06	0.9996 ± 0.0001	99.66% ± 0.06
Wheat	0.389 ± 0.052	0.553 ± 0.078	0.26% ± 0.03	0.9998 ± 0.0001	99.74% ± 0.03

The performance is measured by the per-crop and total performance measures and analyzed with respect to the ability of the model to obtain time realized dependencies, daily patterns and anomalies in crop load behaviour.

5.3 Comparison of CNN-BiLSTM with Previous Models

To evaluate the effectiveness of the proposed CNN–BiLSTM forecasting methodology, a comparative performance analysis was carried out against conventional and deep learning–based forecasting models, namely CNN, LSTM, RBiLSTM, and RNN as recorded in Table 10.

Table 10: Comparison between CNN-BiLSTM and previous models using evaluation metrics.

Model	MAE	RMSE	MAPE (%)	R^2	Prediction Accuracy (%)
CNN-BiLSTM	0.44	0.617	0.3	0.9997	99.7
CNN	4.684	6.916	4.42	0.8914	95.58
LSTM	5.882	7.186	5.53	0.8465	94.47
RBiLSTM	7.022	8.285	6.63	0.7871	93.37
RNN	10.719	12.049	9.09	0.6691	90.91

The CNN-BiLSTM modeled the errors with lower prediction errors with an MAE of 0.44, an RMSE of 0.617 and an MAPE of 0.3 percent as compared to the single CNN model that registered an MAE of 4.684, an RMSE of 6.916 and an MAPE of 4.42 percent. Also, the hybrid model gave a better coefficient of determination ($R^2 = 0.99$) which implies greater strength in reflecting temporal dependencies within the load data. These findings indicate that forecasting using Bidirectional LSTM and CNN-based features is much better than the one based on a traditional CNN model.

As seen in Fig. 16, the CNN model follows with a moderately high R^2 (≈0.89), while the LSTM model shows a noticeable drop, reflecting limited feature extraction capability. The RBiLSTM and RNN models exhibit the lowest R^2 values (below 0.8).

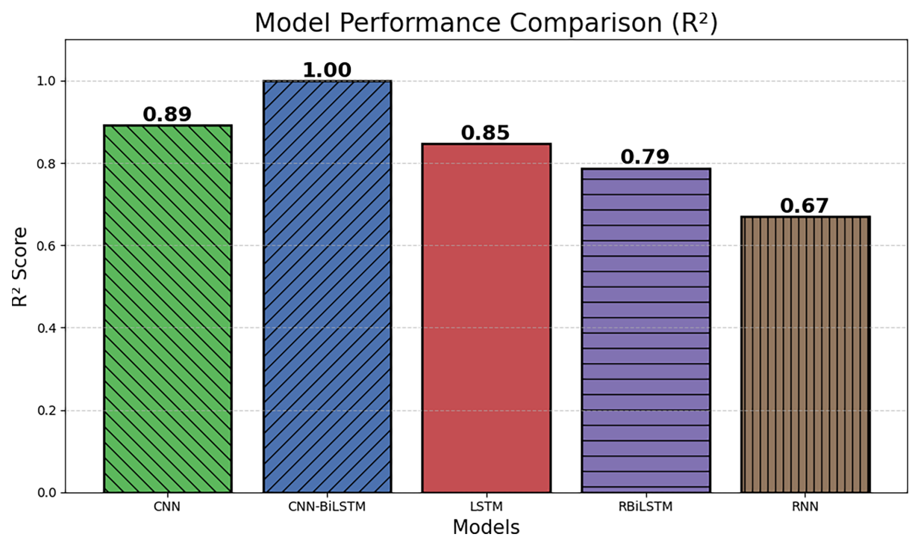


Figure 16: R^2 score comparison across neural network models.

Additional performance analysis collective in terms of MAE, RMSE, and MAPE is indicated in Fig. 17. Based on these error metrics, the CNN-BiLSTM model is invariably associated with the minimum error values which prove the effectiveness and safety of such a model in load prediction.

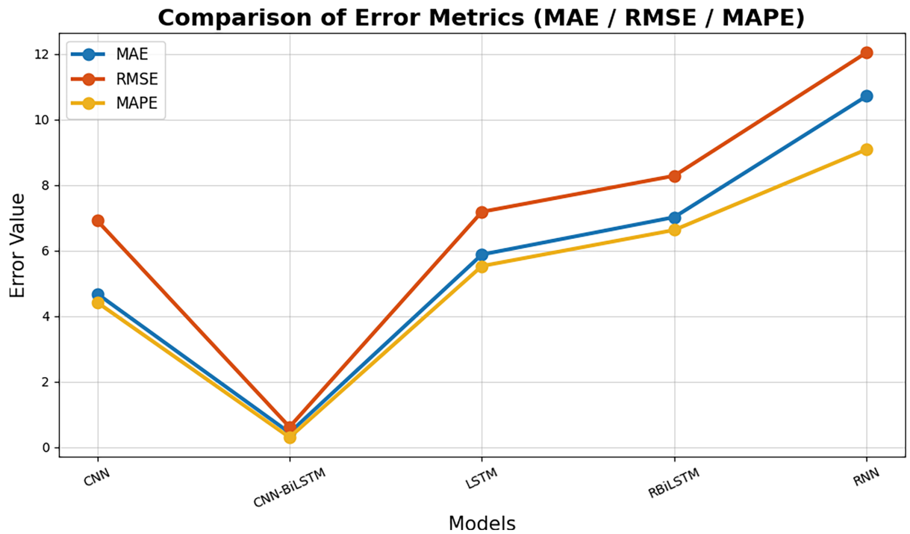


Figure 17: Comparison of error metrics across neural network models.

6 Conclusion

In this paper, a detailed Agricultural Load Forecasting and Scheduling (ALFS) model was proposed to enhance the efficiency of energy consumption and grid stability, as well as stable irrigation of rural agricultural systems. The proposed solution can overcome the drawbacks of the traditional forecasting and heuristic scheduling methods by combining a CNN–BiLSTM–based deep learning forecasting model and a Particle Swarm Optimization (PSO)–based scheduling model, which is less sensitive to nonlinearity, irregular irrigation cycles, dependence on crops, and the lack of closeness in rural areas. The experimental findings based on real data of agricultural electricity consumption in twelve districts of Rajasthan have shown that the proposed forecasting model has low levels of measurement error (MAE, RMSE, MAPE) and performs better than the traditional neural networks, i.e., CNN, LSTM, RBiLSTM and RNN. The model was also found to be able to separate different irrigation demand patterns among different crops (maize, rice, wheat, and sugarcane) to allow specific identification of possible peak-load scenarios. The PSO-based scheduling module then was able to effectively use the forecasted loads to implement grid-compliant and cost-effective irrigation schedules. Altogether, the offered CNN–BiLSTM–PSO scheme represents a powerful, scalable, and applicable solution to the problem of intelligent regulation of energy use in the irrigation systems of agriculture. It allows proper load forecasting on a crop-by-crop basis, active grid balancing, and optimal scheduling of pumps without the need to maintain a constant internet connection. The framework can help utilities and policymakers to mitigate demands during peak periods, minimize operational expenses, and ensure the development of sustainable agricultural activities. This could be expanded upon in the future by adding real-time telemetry, renewable energy integration, adaptive versions of PSO, or reinforcement learning–based control to increase the resilience and autonomy of smart rural power systems.

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Conflicts of Interest: The authors declare no conflicts of interest.

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