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Optimal Resource Planning Using Homer PRO with Monthly Predictions from TCN-based Bidirectional-GRU-LSTM Models

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Abstract:

This paper introduces an innovative approach for optimizing resource allocation in hybrid energy systems by utilizing HOMER Pro, which incorporates monthly load forecasts produced by a Temporal Convolutional Network (TCN)-based Bidirectional-GRU-LSTM (BiGRU-LSTM) model. The proposed technique seeks to overcome the shortcomings of traditional load forecasting methods by employing deep learning strategies to effectively capture both local and long-term dependencies within time-series data. The forecasted load serves as an input for HOMER simulations, facilitating a comprehensive analysis of costs and performance for renewable energy systems. Significant challenges have been identified, such as the static nature of HOMER's load assumptions and the potential for misrepresentation in renewable energy penetration during specific periods. Our findings reveal that although the TCN-BiGRU-LSTM model greatly enhances the accuracy of load forecasting, discrepancies in HOMER's simulations may arise when relying on monthly averaged data, particularly in scenarios with high renewable penetration. The work emphasizes the necessity for more sophisticated simulation frameworks that take into account real-time variations in load and generation data. This research offers important insights into the improvement of hybrid energy system design and optimization through the application of advanced forecasting techniques.

Keywords: Homer Pro, TCN, GRU-LSTM, Time Series Prediction, Renewable Energy Systems, Load Forecasting, Resource Allocation, Optimization

1. Introduction

One of the main challenges in the energy sector today is finding effective ways to utilize renewable energy sources. A solution to this issue is the innovative microgrid concept, which integrates renewable energy sources, distributed generation, and energy storage. Microgrid systems can operate in both connected and isolated modes, offering advantages over traditional power systems. With microgrids, individuals can shift from being mere consumers to active participants as producers in the energy market. Conventional energy markets rely on centralized, long-distance transmission of non-renewable energy, leading to inefficiencies. In contrast, microgrids focus on localized production and consumption of energy. This approach allows for the integration of renewable sources, enhancing energy sustainability and efficiency. Additionally, utilizing diverse energy resources leverages regional potentials, such as solar and wind, promoting increased energy production and a greener future.

In recent years, the shift to renewable energy has driven the need for hybrid energy systems that optimize both renewable and conventional sources. Effective load forecasting is crucial for creating cost-efficient, efficient, and reliable energy systems. Conventional forecasting methods like ARIMA and basic neural networks struggle to account for the complexities in load profiles, especially in renewable energy systems.

This work aims to introduce a forecasting model based on deep learning that employs Temporal Convolutional Networks (TCN) and Bidirectional GRU-LSTM to produce monthly forecasts for load demand. These forecasts are subsequently utilized in Homer Pro to model and enhance resource allocation. By integrating sophisticated predictive modeling with energy system simulation, the objective is to lower overall system expenses and enhance the reliability of hybrid energy systems.

In recent years, advanced machine learning has transformed resource allocation across sectors. Resource allocation in energy systems is vital for efficiency. Advanced computational techniques have improved energy demand forecasting and resource optimization. This literature review examines the use of Homer Pro with advanced forecasting models like TCN and bidirectional-GRU-LSTM for monthly predictions. This integration enhances forecast accuracy and supports better renewable energy deployment, promoting a sustainable energy infrastructure. Additionally, it enables real-time energy distribution adjustments to match changing demand patterns.

Meta-heuristics and deep learning are increasingly used for energy challenges, particularly in optimization and forecasting. Ref[1]emphasises the role of AI in addressing complex energy issues, particularly the uncertainties of renewable energy. The authors point out key research challenges, including enhancing algorithm efficiency and managing larger datasets from various energy systems. [2] examines the role of Artificial intelligence (AI) methods in managing renewable energy through forecasting and resource allocation. The researchers highlighted various machine learning and deep learning methods that tackle non-linear dynamics in such systems. AI's adaptability to real-time data enhances performance and reliability in uncertain conditions.ML and DL methods for building energy simulation and management are tested in [3]. Researchers concluded that supervised, unsupervised, and reinforcement learning models as vital for predicting energy use and optimizing HVAC systems. Moreover, combining DL with optimization algorithms has enhanced forecasting precision and energy efficiency. Deep learning models, in particular LSTM networks, are widely used in energy forecasting for their time-series capabilities [4]suggesting an improved alpha value for LSTM models to boost energy usage forecasting accuracy. The research highlights that deep learning models are better than traditional methods for large-scale, high-dimensional energy data.[5-6] highlights how ML models can improve the efficiency and reliability of energy systems when dealing with the variables of sources like solar and wind. The importance of enhancing energy distribution and storage decisions, transforming urban energy planning by making systems more responsive to real-time needs. However, there is a necessity for stronger models that can manage diverse urban energy systems and provide more accurate demand forecasts. Recent advancements in optimization, such as LSTM models with PSO and grid search, have been investigated [7-10]. These optimized models enhance time series forecasting performance for energy demand, revealing that hybrid methods can boost accuracy and robustness. The literature proved that deep learning models outperform traditional forecasting but call for more generalized models applicable to various energy sources. [11-13] investigated RNN architectures like LSTM and GRU for predicting energy consumption in multivariate time series and emphasised their advantages in optimizing grid operations and promoting renewable energy policies.

[14-15]provides optimized hybrid solar PV-wind-battery systems in remote areas with Homer Pro, showing reduced energy costs and fossil fuel dependence. Homer Pro facilitates simulations to determine the most cost-effective system designs based on geographical and economic factors. They demonstrated that enhancing renewable energy use can decrease reliance on diesel generators and mitigate environmental effects. However, such studies depend on historical or static data for load demands, which may delay system adaptability to changes. Employing accurate, real-time load forecasting methods can improve system efficiency by aligning energy generation and storage with anticipated future demands. Load forecasting is essential for energy demand assessment and resource optimization. Traditional forecasting methods struggle with complex patterns and non-linearity, making them less suitable for today's energy systems. In [16] deep learning models like GRU and LSTM capture non-linear patterns in renewable energy data from traditional methods by handling long-term dependencies effectively. Despite their advantages, integrating these predictive models with optimization tools like Homer Pro is still developing. There is great potential to enhance resource planning and allocation in energy systems through this integration.

Temporal Convolutional Networks (TCNs) serve as an effective alternative to recurrent neural networks like GRU and LSTM for forecasting time series. They utilize causal convolutional layers, making them ideal for sequence tasks such as load forecasting. [17-18]discusses the superiority of TCNs in capturing both short-term and long-term patterns in energy load data makes TCNs highly suitable for dynamic energy systems. Although TCNs excel at extracting temporal features, GRU and LSTM are effective at maintaining long-term memory, which is necessary for modelling sequences with significant temporal dependencies. Combining these models into hybrid architectures influences the strengths of each, improving overall forecasting performance. [18-20] discussed the importance of combining TCN’s ability to model temporal relationships with GRU’s efficiency in handling sequential dependencies. The combination of TCN, GRU, and LSTM represented a promising path for improving load forecasting accuracy in hybrid energy systems. Therefore these techniques when integrated with energy system simulation tools like Homer Pro, these models can significantly enhance the system's ability to optimize resource allocation based on accurate demand predictions. [21] hybrid energy system optimization with integrated LSTM load forecasting with Homer Pro indicated that predictive load models increased simulation accuracy and lowered both Net Present Cost (NPC) and Levelized Cost of Energy (LCOE). LSTM models facilitated improved planning for energy storage and renewable generation, decreasing reliance on non-renewable sources. Although there is growing interest in deep learning and optimization integration, TCN-based hybrid models with Homer Pro are still underexplored. Integrating TCN-GRU-LSTM models with Homer Pro may enhance load prediction accuracy and lead to more cost-effective, reliable energy systems. Nevertheless, a significant drawback of HOMER is its dependence on fixed assumptions regarding future load distributions, which may result in errors when modelling complex systems with varying energy requirements.

Hence the objective of this paper is to examine the incorporation of a TCN-based Bidirectional-GRU-LSTM model for predicting monthly loads, which subsequently serve as inputs for HOMER simulations. The paper analyses the benefits of this methodology regarding forecasting precision, as well as the possible limitations associated with HOMER's rigid treatment of monthly load inputs. Through various case studies and simulation outcomes, it demonstrates how this combined approach can improve the planning and optimization of hybrid energy systems, while also pinpointing critical areas where additional enhancements are necessary to manage real-time variability and the integration of renewable energy sources. In this research real-time load data for the year 2023 is considered from the available reports on the website of the Andhra Pradesh State Load Despatch Centre [22]. This paper provides a framework using monthly predictions from the TCN-based Bidirectional-GRU-LSTM model for resource allocation through Homer Pro Simulations.

2. Overview of Homer Pro

For the design, planning, and simulation of the microgrid model, the HOMER Pro software offers numerous advantages. These advantages encompass its capacity to integrate various renewable energy sources along with multiple other elements essential for a stable microgrid model. The software is highly proficient in assessing both the economic and technical viability of the model under constrained circumstances [23-24]. Figure 1 illustrates the step-by-step workflow of HOMER Pro software, highlighting its diverse components.

2.1 Economic Aspects

Net Present Cost (NPC)

The NPC reflects the total expenses of a system, minus the revenues earned during its lifetime. Expenses include capital costs, replacement costs, O&M costs, fuel costs, emission penalties, and grid power purchases. Revenues are derived from salvage value and grid sales. HOMER calculates the total NPC by summing the discounted cash flows for each project year during project's lifespan.

Total Annualized Cost (TAC)

It indicates the yearly total net present cost. The annualised cost reflects the expense equal to the net present cost if spread evenly throughout the project. HOMER calculates the annualized cost by finding the net present cost and multiplying it by the capital recovery factor (CRF).

$$\mathbf{C_{ann,tot} = CRF(i, R_{proj}).\, C_{NPC,tot}} \qquad (1)$$

where,

‘$C_{(NPC,tot)}$’= the total NPC
‘I’ = the annual real discount rate [%]
‘R_{proj}’= the project lifespan [yr]
‘CRF ()’ = the function returning the CRF

Simple payback

It reflects the number of years necessary for the cumulative cash flow generated from the difference between the current system and the base case system to turn positive. The payback period demonstrates the time required to recover the investment cost difference between the current system and the base case system.

Return on Investment (ROI)

The annual savings associated with the initial investment. ROI signifies the yearly average fluctuation in nominal cash flows throughout the project, divided by the capital expenditure.

Operating Cost

It is defined as the mathematical relationship between the total annualized cost of the component and its overall capital investment. The evaluation of operating costs delivers the analytical worth of the component while excluding its initial capital and installation costs.

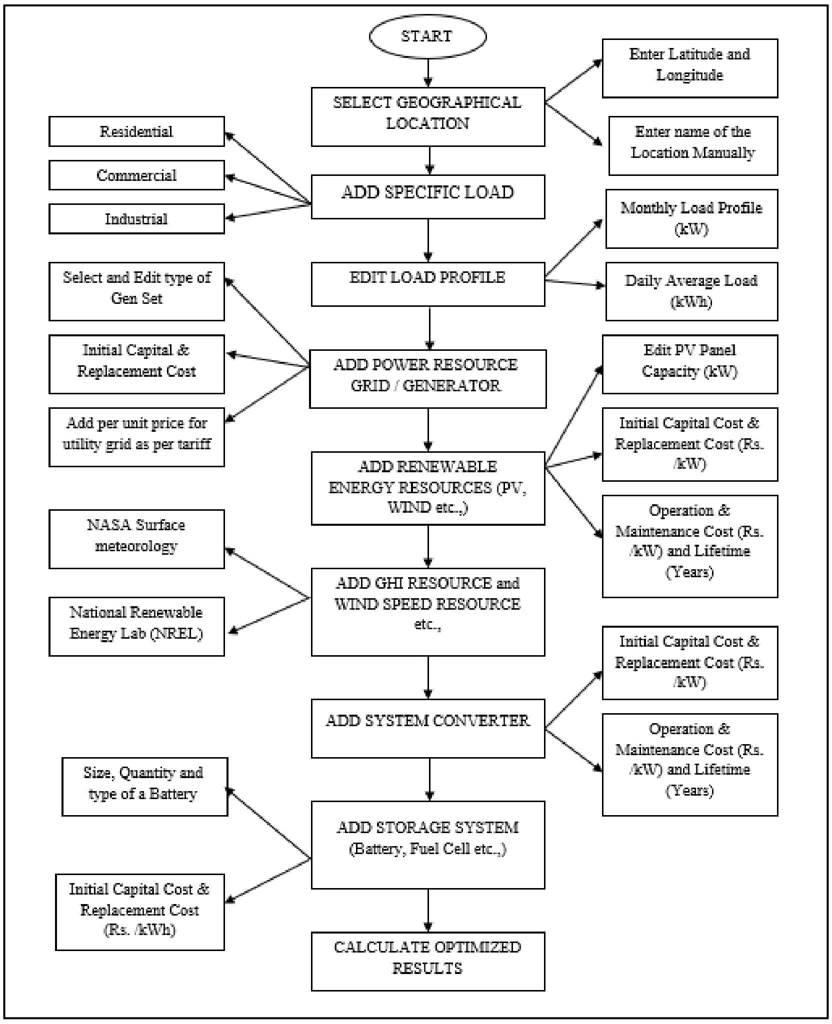


Fig.1 Working Flow of Homer Software.

$$\mathbf{C}_{\mathbf{operating}} = \boldsymbol{C}_{\mathbf{ann,tot}} - \mathbf{C}_{\boldsymbol{ann,cap}} \qquad (2)$$

where,

'$C_{ann,tot}$'= total annualized cost (Rs. per yr)

'$C_{ann,cap}$' = total annualized capital cost (Rs. per yr)

2.2. TCN-Bidirectional GRU-LSTM Model

The combination of Temporal Convolutional Networks (TCN) with Bidirectional Gated Recurrent Units (BiGRU) and Long Short-Term Memory (LSTM) networks marks a notable improvement in sequence modelling, especially for tasks needing long-range dependency capture.

2.2.1 Model Architecture

The TCN-based Bidirectional GRU-LSTM model effectively captures temporal dependencies in historical load data. The following is the learning framework.

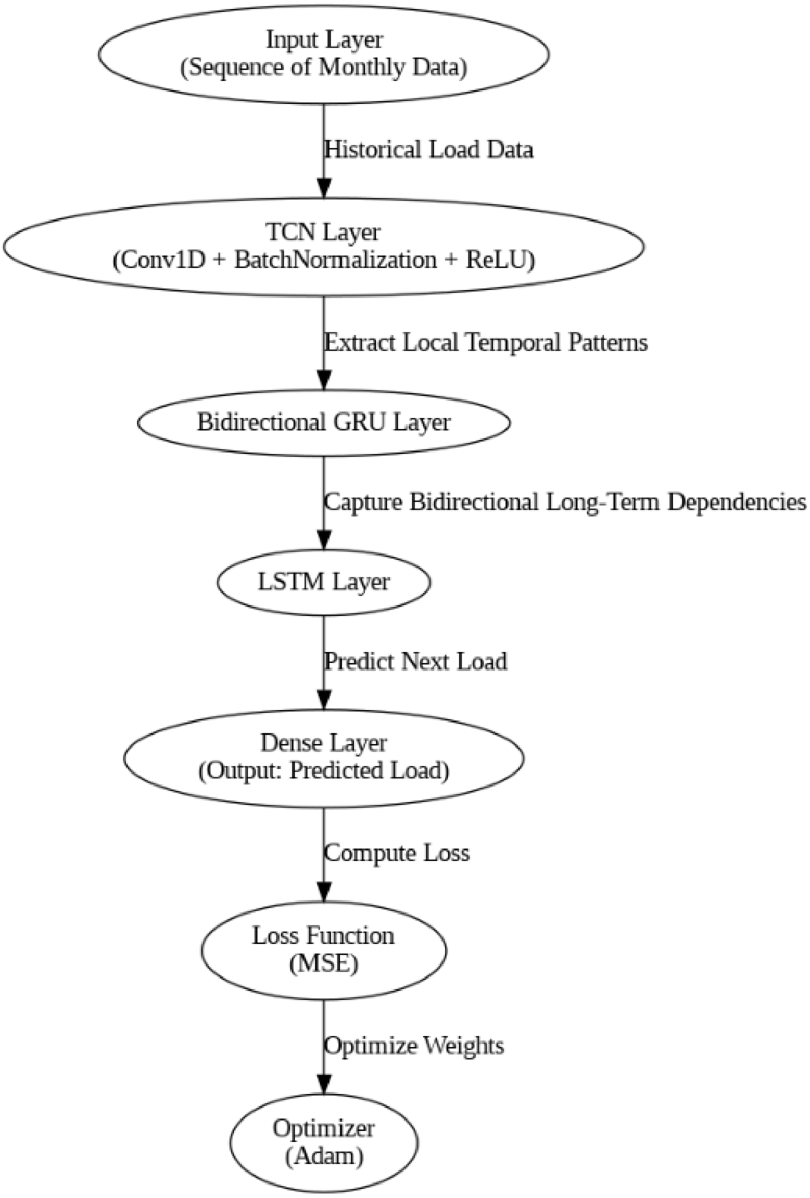


Fig.2 Learning Framework of TCN-Based BiGRU-LSTM for monthly Load Forecasting

The proposed learning framework integrates a Temporal Convolutional Network (TCN), Bi-GRU, and LSTM for monthly load forecasting. Fig.2 illustrates the data's progression through the model, highlighting its various layers and components. This proposed framework leverages the advantages of Temporal Convolutional Networks (TCNs) for localised temporal structures and Bidirectional Gated Recurrent Unit-Long Short-Term Memory (GRU-LSTM) layers for long-term dependencies, making it exceptionally suitable for time series load forecasting.The complete process implemented in this paper is as follows:

i) Input Layer: The input consists of a sequence of monthly historical data for load forecasting.

a. Time Series Data and Resampling: A time series refers to the sequence of data points gathered at particular time intervals. This paper considers electrical load data throughout time. The objective is to forecast forthcoming values based on previous observations. The data is then converted from its initial frequency for instance, “daily or hourly” to a “monthly” frequency to identify long-term trends. Resampling is essential to highlight broader patterns instead of minute variations.

b. Normalization*:* Machine learning models typically yield improved results when features are scaled comparably. Eq.(3) describes how “MinMaxScaler” adjusts the features by normalizing each value within a range of 0 to 1. In time series forecasting, normalization guarantees that varying value ranges do not unfairly influence the learning process. The application of “MinMaxScaler” guarantees that the data is uniformly scaled, avoiding the scenario where specific values overpower the loss function owing to significant magnitude disparities.

$$Xnormalized = \frac{X-Xmin}{Xmax\ -Xmin} \qquad (3)$$

c. Sequence Generation*:* Time-series forecasting challenges necessitate utilising prior observation sequences to estimate upcoming values. The sliding window technique generates overlapping data sequences (windows) that represent a continuous context. Time-series data exhibits temporal relationships, indicating that upcoming values are influenced by preceding values. Sequences embody this relationship, and deep learning models are capable of analysing these sequences to identify patterns and trends. For sequence generation, consecutive time steps are used and consider sequence length ‘S’, for each time ‘t’. Therefore, features for time ‘t’ are in eq(4) &eq(5) that are done for each time step ‘t’ where t > S.

$$X_t = [X_{t-s}, X_{t-S+1}, \dots\dots, X_{t-1}] \qquad (4)$$

and the label for time ‘t’ is defined as $y_t = X_t$ (5)

d. Train-Test Split: In contrast to standard machine learning scenarios that utilize random sampling for data division, in time series analysis, “shuffle=False” guarantees that the chronological sequence remains intact. Here, shuffling is avoided since future values need to rely on preceding values.

ii) Model Architecture

a. Temporary Convolution Layer (TCN) Layer: The TCN is a convolutional neural network that extracts high-level temporal features from the input sequence, allowing for more effective modelling of long-range dependencies in the data. A one-dimensional convolution layer is employed to detect “local temporal patterns” within the time series data. It utilizes convolutional filters to reveal short-term dependencies by examining neighbouring time steps. Convolutions excel at identifying patterns such as trends and seasonality. The causal padding guarantees that the convolution does not “observe” future data, preserving the proper temporal sequence.

$$X_{conv}(t) = \sum_{k=0}^{K-1} W_k * X(t-k) \qquad (6)$$

Where

- W_k are the kernel weights of convolution
- k is the kernel size
- X(t-k) are the inputs at different time steps
- $X_{conv}(t)$ is the convolved output

b. Batch Normalization and ReLU Activation: The normalization process standardizes the results from the convolutional layer as in eq(7), accelerating convergence in training and enhancing model stability by mitigating internal covariate shifts. ReLU adds non-linearity to the model, allowing it to recognize intricate patterns. It directly transmits the input when it is positive; if not, it returns zero by effectively avoiding saturation problems where gradients diminish excessively.

$$X_{BN} = \gamma * \frac{X-\mu}{\sigma} + \beta \qquad (7)$$

Where

- μ is the mean of the batch
- Σ is the standard deviation
- γ & β are learning parameters

c. Bidirectional GRU Layer: Gated Recurring Unit (GRU) is a type of recurrent neural network (RNN) that is specifically engineered to grasp temporal dependencies within sequential data. GRU employs gating mechanisms to regulate the flow of information, thus preventing the vanishing gradient issue in extended sequences. Bidirectional GRU (BiGRU) analyzes the input in both forward and backward directions. This enables it to learn from both past and future contexts in the sequence, although caution is necessary when applying it to strictly forward-looking forecasting, precautions are taken to prevent future data leakage. A GRU calculates the hidden state at each time step. The forward and backward GRUs are derived as in eq(8-10)

$$h_t^{forward} = GRU\left(X_t, h_{t-1}^{forward}\right) \qquad (8)$$

$$h_t^{backward} = GRU\left(X_t, h_{t+1}^{backward}\right) \qquad (9)$$

$$The\ output\ is\ a\ concatenation\ of\ the\ forward\ and\ backward\ states$$

$$h_t = \left[h_{t-1}^{forward}, h_{t+1}^{backward}\right] \qquad (10)$$

Long Short-Term Memory (LSTM) Layer: LSTM is another variant of RNN that is particularly adept at capturing “long-term dependencies” within data, effectively addressing the vanishing gradient issue through its gating mechanisms (input, forget, and output gates). LSTMs preserve a memory of significant previous data points over extended sequences, making certain that long-term trends in the time series are taken into account. In time series forecasting, the significance of long-term dependencies cannot be overlooked. For example, seasonality such as yearly cycles can be identified through LSTM layers, as they efficiently preserve historical information. LSTM updates the cell state and hidden state for each time step as in eq(11-15) where ‘f_t’, ‘i_t’ , ‘o_t’ are the forget, input and out gates respectively.

$$f_t = \sigma * \left(W_f * [h_{t-1}, X_t]\right) + b_f \qquad (11)$$

$$i_t = \sigma * (W_i * [h_{t-1}, X_t] + b_i) \qquad (12)$$

$$\tilde{C}_t = tanh(W_C * [h_{t-1}, X_t] + b_C) \qquad (13)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \qquad (14)$$

$$h_t = o_t * tanh(C_t) \qquad (15)$$

d. Dense Layer(Output Layer): A Fully Connected Layer that converts the features learned from earlier layers into a singular output value. This output signifies the anticipated load for the forthcoming time step. It synthesizes all the knowledge gained from earlier layers to arrive at the ultimate prediction.

$$y_{pred} = W_{dense} * h + b_{dense} \text{-------(16)}$$

Where

- W_{dense}*are the weights of dense layers*
- b_{dense}*is the bias term*
- *h is the hidden state from previous layer*

2.2.2 Training Process, Prediction and Evaluation

a. Loss Function: The model is developed using the "Mean Squared Error (MSE)" loss function specified in eq(17). This loss function is commonly employed in regression tasks, measuring the average squared difference between predicted outcomes and actual target values. By reducing MSE, the model's predictions gradually become more consistent with actual values over time.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_{actual,i} - y_{pred,i}\right)^2 \qquad (17)$$

Where

- y_{actual}, actual load
- y_{pred}, predicted load
- N, number of samples

b. Optimizer: The “Adam” optimizer is employed for training, representing a modified approach to gradient descent that adjusts the learning rate of 0.001 for every parameter, resulting in quicker convergence as in eq(18-20). Adam merges the benefits of two additional techniques: RMS Prop and momentum.

$$m_t = \beta_1 * m_{t-1} + (1 - \beta_1) * g_t \qquad (18)$$

$$v_t = \beta_2 * v_{t-1} + (1 - \beta_2) * g_t^2 \qquad (19)$$

$$\theta_t = \theta_{t-1} - \alpha * \frac{m_t}{\sqrt{v_t + \epsilon}} \qquad (20)$$

Where

- g_t, gradient at time step t
- m_t, first moment estimate
- v_t, second moment estimate
- θ_t, weights being updated
- *α is the learning rate*
- *β_1,β_2 are initial decay rates*

c. Hyperparameter Tuning*:* Keras Tuner is used to enhance the count of units in both the GRU and LSTM layers, adjust the learning rate, and determine the batch size.

d. Prediction and Evaluation: Once the model has been trained, it is employed to forecast the load values for the test dataset. This process involves inputting the test sequences into the trained model.

2.2.3 Pseudocode

```
1. Load data from CSV
2. Parse Datetime-column and set it as index
3. Resample data to monthly frequency
```

```
4. Normalize data using MinMaxScaler
5. Create sequences:
    • For ‘i’ in range(len(data) - SEQ_LENGTH)
    • X.append(data[i:i+SEQ_LENGTH])
    • y.append(data[i+SEQ_LENGTH])
    • Return X, y as arrays
6. Split X, y into training and testing sets (80% train, 20% test)
7. Build model:
    • Input layer characterized by dimensions (SEQ_LENGTH, num_features)
    • Convolutional 1D layer incorporating 64 filters
    • Batch normalization accompanied by ReLU activation function
    • bidirectional Gated Recurrent Unit (GRU) layer comprising 64 units
    • LSTM layer consisting of  64 units
    • Dense output layer featuring a single unit
    • Compile model to minimise MSE Loss using Adam optimizer
8. Train model for 50 epochs and validate on test set with batch size 32
9. Predict on test set
10. Inverse scale y_test and y_pred back to original scale
11. Plot actual vs predicted values for test set
12. Save predicted values to a CSV file
```

2.3. Incorporating Forecasts into Homer Pro

The monthly forecasts produced by the TCN-Bidirectional GRU-LSTM model are incorporated into Homer Pro as input for the load profile. Subsequently, Homer Pro evaluates the system's performance across different scenarios and optimizes the allocation of resources based on the predicted monthly load from the TCN-Bidirectional GRU-LSTM model and Fig.3 is the generated daily load profile. The optimal resources are obtained via simulating the proposed architecture in Fig.4 The simulation scenarios are as follows:

2.3.1 Baseline Scenario: The electric needs of the system shown in Table.I is predicted to be met with 7,700,000 kW of generator capacity. Your operating costs for energy are currently \$8.13B per Year over 25 year project life.

Table.I Details of the current system

Base Case	**Latitude**	**Longitude**	**Operating Cost/Year**
	16^{0}30’.4”	80^o 38’9”	\$8.13B

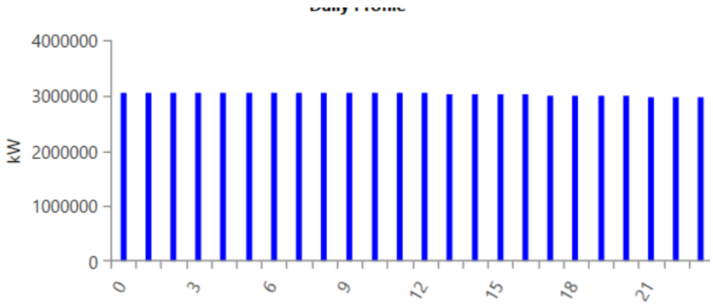


Fig.3 Daily Load Profile

2.3.2Prediction-Based Scenario: This work is proposed to incorporate 22,819 kW of photovoltaic power and 184 kWh of energy storage capacity. This implementation would bring the annual operating expenses down to $526 million. The return on investment is calculated to be 0.000829 years. Fig. 4 illustrates the schematic representation of the proposed system along with the available resources. The specifics of the available resources are outlined in the following discussion.

a. PV: Canadian solar Dymond CS6K-285M-FG: Table II delineates the specifications of the Canadian Solar photovoltaic system, which possesses a nominal capacity of 2,819 kilowatts(kW). The annual energy output is quantified at 4,400,532 kilowatt-hours per annum(kW/yr).

Table.II Optimized results of Canadian solar Dymond CS6-285M-FG

Rated Capacity	2819 kW		Total Production	4400532 kW
Capital Cost	$440M		Maintenance Cost	131913 $/yr
Specific Yield	1561 kWh/kW		LCOE	0.107 $/kWh
PV Penetration	0.210 %			

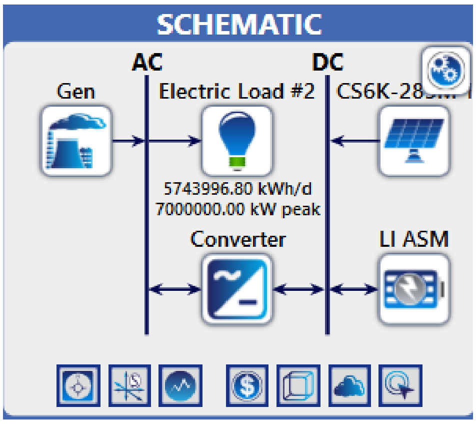


Fig.4.Schematic diagram of the Proposed system

b. Generator: Autosize Genset (Diesel): Table III illustrates that the power output generated by the Generic generator system, which is rated at 7,700,000 kW utilizing Diesel as the fuel source, amounts to 2,108,249,728 kWh per annum.

Table.III Optimized results of Generic generator system

Capacity	7,700,000 kW		Generator Fuel	Diesel
Operational Life	46.4 yr		Generator Fuel Price	1.00 $/L
Capital Cost	$3.85B		Maintenance Cost	24,871,000 $/yr

Fuel Consumption	533,978,272 L		Electrical Production	2,108,249,728 kWh/yr
Hours of Operation	323 hrs/yr		Marginal Generation Cost	0.236 $/kWh
Fixed Generation Cost	446,616 $/hr			

c. Storage: Generic 1kWh Li-Ion: Table IV presents information indicating that the nominal capacity of the Generic storage system is 184 kWh. The yearly throughput amounts to 32,545 kWh per year.

Table.IV Optimized results of Generic Storage System

Rated Capacity	184 kWh		Expected Life	15.0 yr
Annual Throughput	32,545 kWh/yr		Capital Costs	$99,158
Maintenance Cost	1,611 $/yr		Losses	3,180 kWh/yr
Autonomy	0.000538 hr			

d. System Converter: Table.V provides the details of System converter that has a capacity of 29.2kW

Table.V Optimized results of System Converter

Capacity	29.2 kW		Hours of Operation	8,580 hrs/yr
Mean Output	7.22 kW		Energy Out	63,237 kWh/yr
Minimum Output	0 kW		Energy In	66,565 kWh/yr
Maximum Output	29.2 kW		Losses	3,328 kWh/yr
Capacity Factor	24.7 %			

3. Results and Discussion

3.1 Performance of the proposed model:

The TCN-Bidirectional GRU-LSTM model demonstrates superior performance in predicting monthly load data when compared to traditional methods such as LSTM by tuning with the hyperparameters as in table.VI. The model has been configured using the Adam optimizer along with mean squared error (MSE) as its loss function. MSE quantifies the mean of the squared discrepancies between the actual values and the predicted outcomes. The model achieves a **Root Mean Squared Error (RMSE)** of 0.1071 and a **Mean Absolute Percentage Error (MAPE)** of 0.1073%, outperforming baseline models by a significant margin.Fig.5 shows the comparison of actual and predicted monthly load.

Table.VI List of hyperparameters for the proposed model

S.No	**Hyperparameters Considered**

1	Filter Size	Conv1D for 64 filters
2	No.of Units	GRU and LSTM layers use 64 units
3	Kernel size	Conv1D-3
4	Learning Rate	0.001
5	Batch size	32
6	Number of Epochs	50

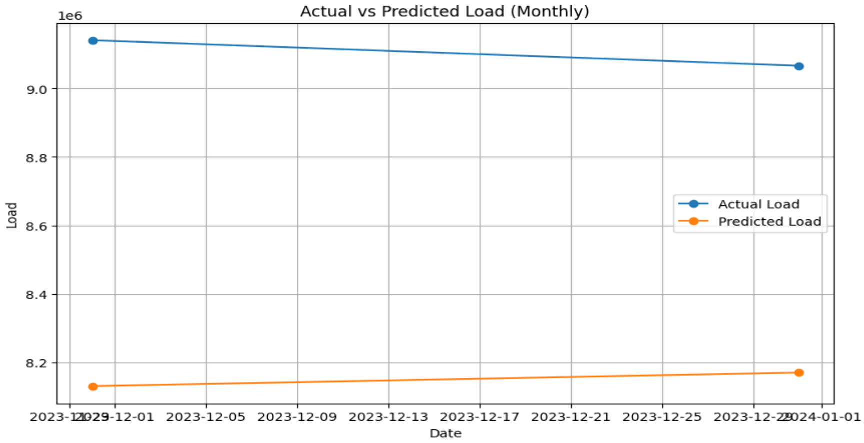


Fig. 5Actual Vs Predicted Monthly Load using TCN based BiGRU-LSTM

3.2 Homer Pro Simulation Results

The overall NPC for each scenario has been documented. To achieve the goals, the cost ramifications of all scenarios were analyzed in this research. For the simulation, the sizes of the system components were modified in accordance with the established constraints, and the results were summarized in Table-III based on the lowest NPC value. HOMER evaluates the results of every possible combination of resources for the predicted monthly load. In this research, two alternative models were assessed. After comparing the base case and proposed case significant findings from Table VII include:

- **Resource Allocation**: The proposed system setup incorporates a greater dependence on solar PV and battery storage based on the predicted load data, thereby minimizing reliance on diesel generators reducing the fuel consumption
- **Cost Savings**: The system that incorporates load forecasts realizes reduced operational expenses, more effective synchronization of renewable energy production with anticipated demand reduced the NPC to $10.6B and operating cost to $0.394/kWh

Table.VII Simulation results for optimal resource planning

		Base Case	**Proposed Case**
Cost	NPC ($)	109B	10.6B
	COE ($)	4.02/ kWh	0.394/ kWh
	Operating Cost ($yr)	8.13B/Yr	526M/yr

	Initial capital ($)	3.85B	3.85B

3.3 Time Series Simulation Results

The daily production of the power from PV in Fig.6is observed to be 4,400,532 kW and Fig.7 shows that the daily production of power from the generator and the total production is 7,700,000 kW. Fig .8 represents that the state of charge(SOC) of the battery at 4AM on 18th February is 53.97%. Fig.9 is showing that the SOC of battery is 100% at 11AM on 8th January. The results presented in Fig10-Fig13 are a comparison between time series analysis plots of total electrical load served, Renewable Penetration, Generic 1kWh Li-ion(ASM) State of Charge, Auto genset power output, Generic 1kWh Li-ion(ASM) Discharge Power, AC Primary Load Served, AC Primary Load, Renewable power Output in different months at various timings on different days.

Table.V III Comparative Time series Analysis

Sl.No	Description	Saturday 4AM on 18th February	Sunday 11AM on 8th January	Sunday 12PM on 16th July	Tuesday 6PM on 25th December
1	total electrical load served,	7.00KW	6999998KW	7KW	7.00KW
2	Renewable Penetration,	0%	0.02%	26887.75%	0%
3	Generic 1kWh Li-ion(ASM) State of Charge,	53.97%	100%	100%	95.74%
4	Auto genset power output,	0KW	6999970KW	0KW	0KW
5	Generic 1kWh Li-ion(ASM) Discharge Power,	7.37KW	134.06KW	132.58KW	131.38KW
6	AC Primary Load Served,	7.00KW	6999998KW	7.00KW	7.00KW
7	AC Primary Load,	7.00KW	6999998KW	7.00KW	7.00KW
8	Renewable power Output	0KW	1570.1KW	1882.14KW	

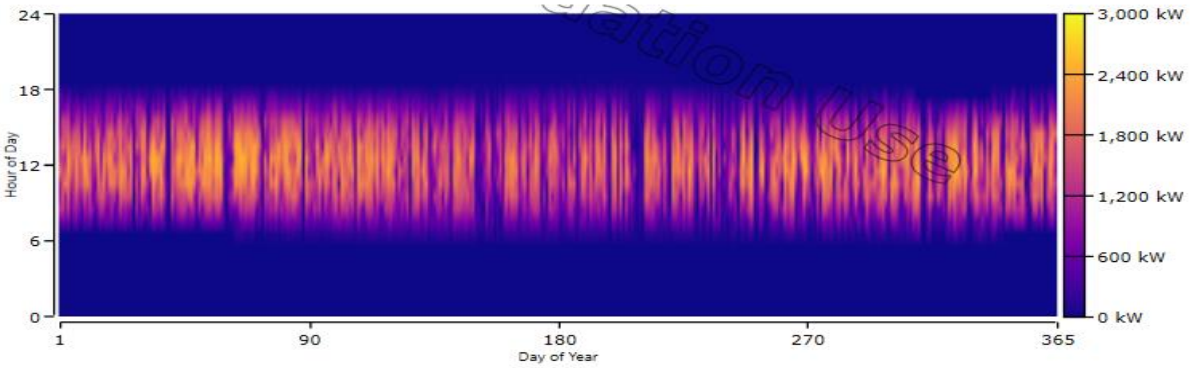


Fig.6 Daily production of the power from PV

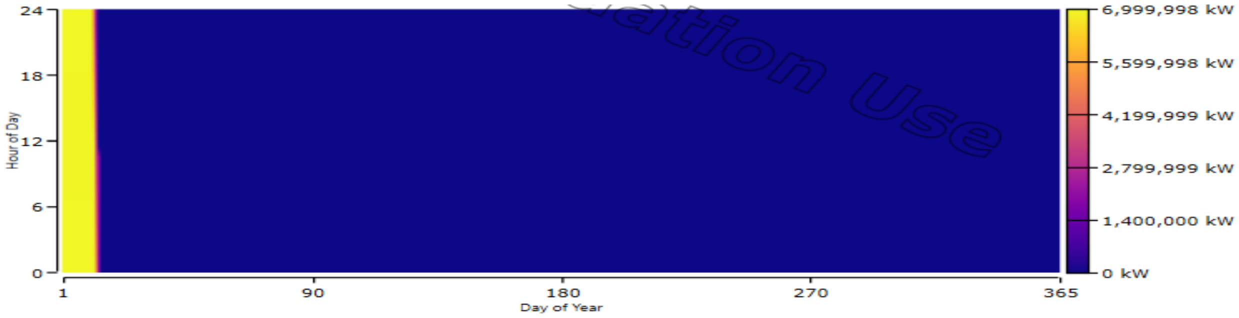


Fig.7 Daily production of the power from Generator

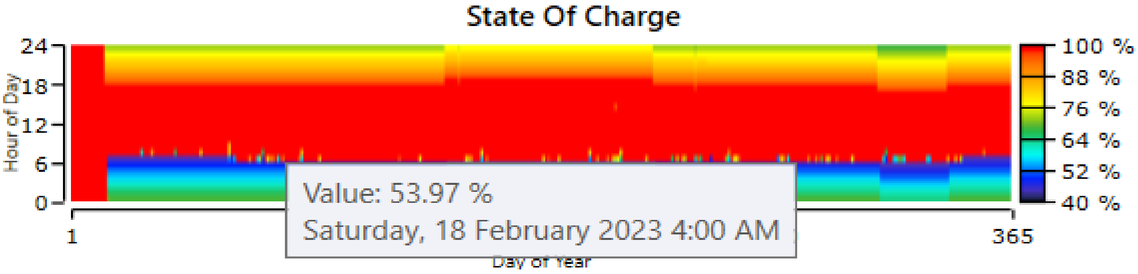


Fig.8 State of Charge of the Battery at 4.00AM in February

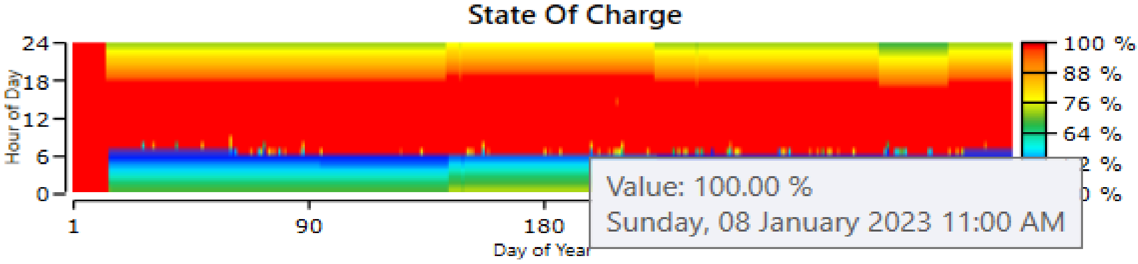
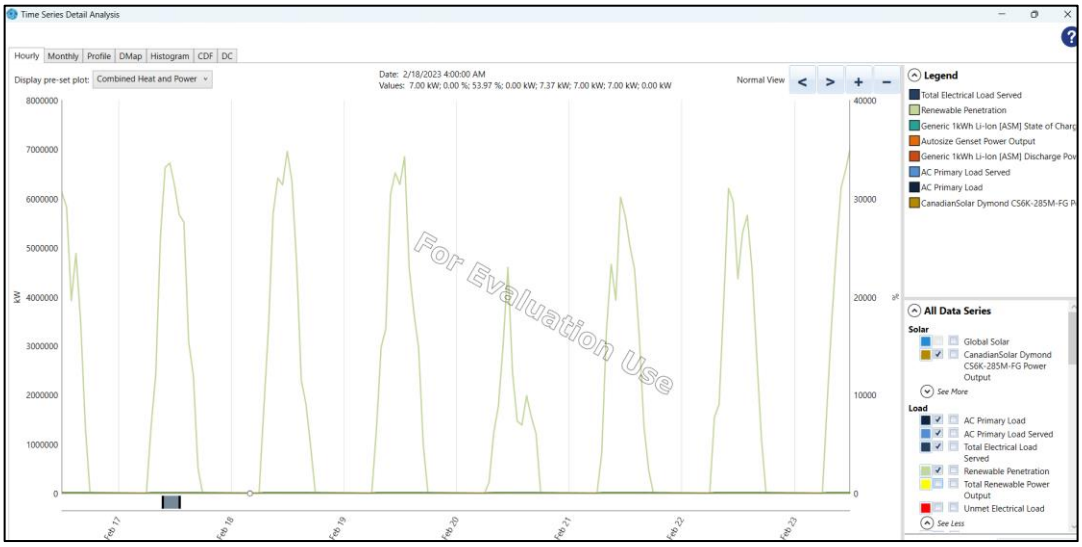


Fig.8 State of Charge of the Battery at 11.00AM in January



Display pre-set plot: Combined Heat and Power

Date: 2/18/2023 4:00:00 AM
Values: 7.00 kW; 0.00 %; 53.97 %; 0.00 kW; 7.37 kW; 7.00 kW; 7.00 kW; 0.00 kW

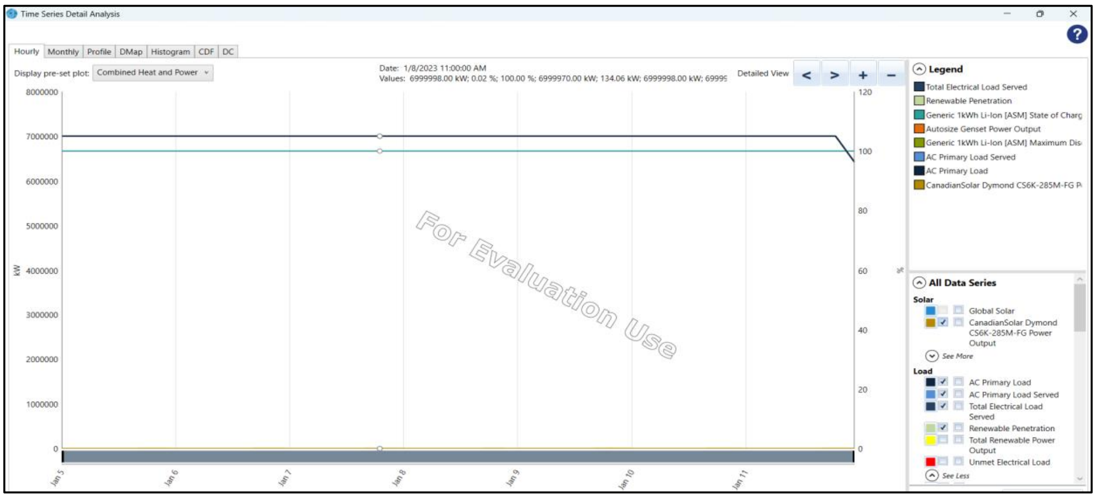
Legend
- Total Electrical Load Served
- Renewable Penetration
- Generic 1kWh Li-Ion [ASM] State of Charg
- Autosize Genset Power Output
- Generic 1kWh Li-Ion [ASM] Discharge Pow
- AC Primary Load Served
- AC Primary Load
- CanadianSolar Dymond CS6K-285M-FG P

All Data Series

Solar
- ☐ ☐ Global Solar
- ☑ ☐ CanadianSolar Dymond CS6K-285M-FG Power Output

Load
- ☑ ☐ AC Primary Load
- ☑ ☐ AC Primary Load Served
- ☑ ☐ Total Electrical Load Served
- ☑ ☐ Renewable Penetration
- ☐ ☐ Total Renewable Power Output
- ☐ ☐ Unmet Electrical Load

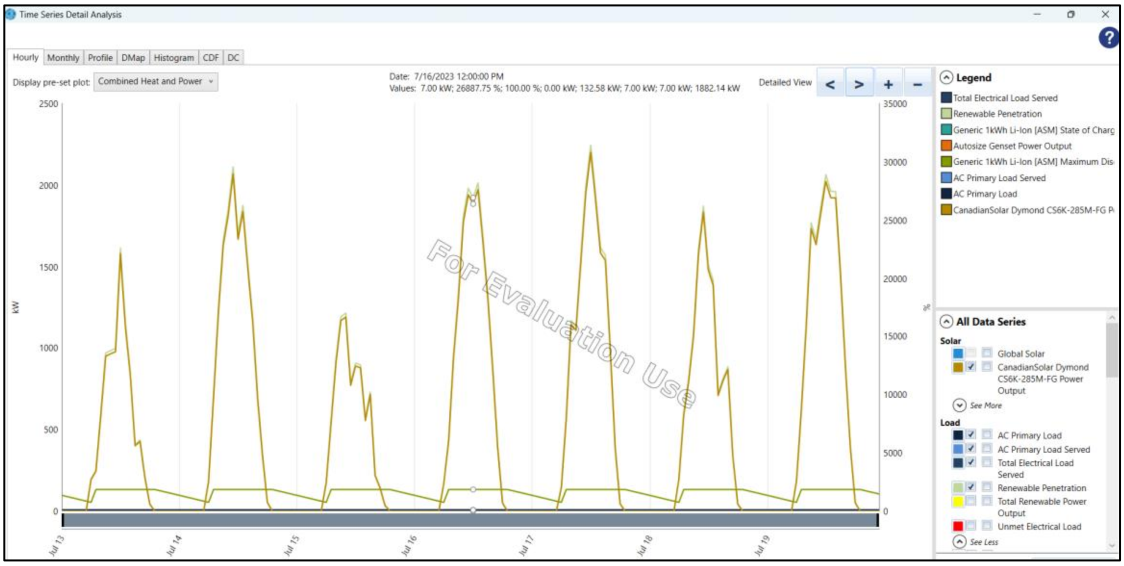
Fig.10 Time series Analysis at 4.00AM February



Display pre-set plot: Combined Heat and Power

Date: 1/8/2023 11:00:00 AM
Values: 6999998.00 kW; 0.02 %; 100.00 %; 6999970.00 kW; 134.06 kW; 6999998.00 kW; 69999

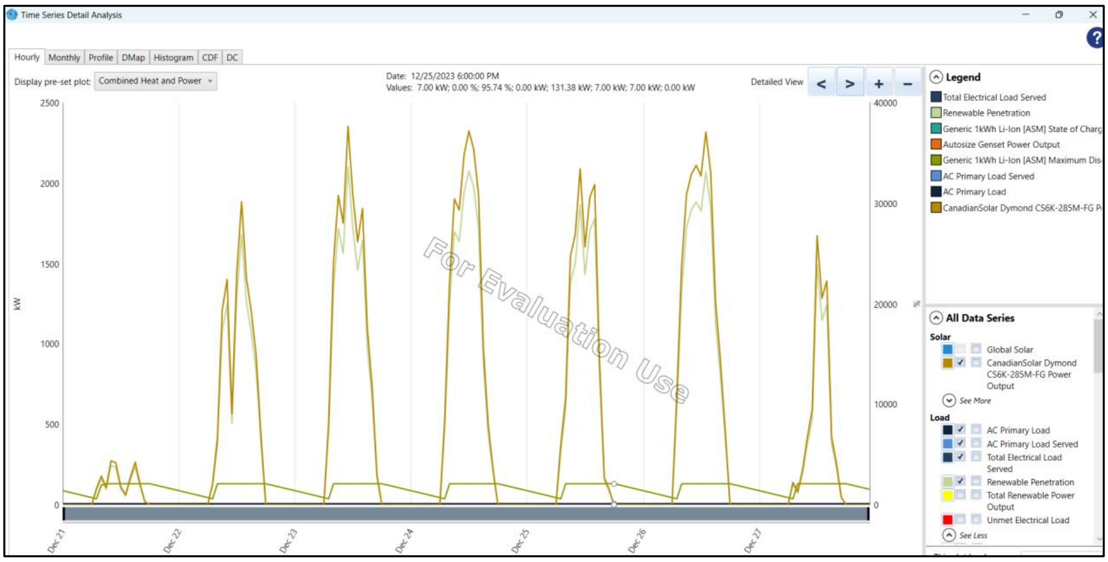
Fig.11Time Analysis at 11.00AM January



Display pre-set plot: Combined Heat and Power

Date: 7/16/2023 12:00:00 PM
Values: 7.00 kW; 26887.75 %; 100.00 %; 0.00 kW; 132.58 kW; 7.00 kW; 7.00 kW; 1882.14 kW

Fig.12 Time Analysis at 12.00PM July



Display pre-set plot: Combined Heat and Power

Date: 12/25/2023 6:00:00 PM
Values: 7.00 kW; 0.00 %; 95.74 %; 0.00 kW; 131.38 kW; 7.00 kW; 7.00 kW; 0.00 kW

Fig.13 Time Analysis at 6.00PM December

3.4 Observations and Findings:

The monthly load forecasts used for HOMER simulations are derived from a TCN-based BiGRU-LSTM model. This approach provides an in-depth understanding of anticipated energy requirements. Nonetheless, there are many limitations associated with employing such forecasts in HOMER simulations. To overcome these limitations in HOMER, it is essential to continuously observe actual load patterns and regularly revise load forecasts. The following are the observations and findings from the proposed work

i. HOMER presumes that load patterns will exhibit comparable trends in the upcoming months, which do not need to be correct. This constrains the adaptability of the simulation when real load patterns diverge from the predicted model's expectations.
ii. HOMER evaluates the share of renewables based on the existing load and the generation of renewable energy. When the forecasted load fluctuates drastically as seen in Table.VIII with a 26887.75% penetration. This depicts an inflated or unrealistic representation of renewable energy efficacy.
iii. While the proposed TCN-based BiGRU-LSTM model effectively incorporates historical data, HOMER fails to adjust to swift alterations in external factors such as seasonality, economic changes, or policy shifts that could influence energy consumption trends in real-time.
iv. The TCN-based BiGRU-LSTM models excel in making short-term predictions, but their accuracy may decline when it comes to long-term monthly forecasts. This discrepancy could lead to differences between the actual load and the predicted load, which HOMER utilizes as a fundamental reference for its simulation.
v. HOMER assumed that the responses of storage and generators are closely linked to the predicted load. If the predicted load varies considerably from the actual conditions, it results in inadequate or impractical sizing of energy storage solutions and generators.
vi. HOMER's deterministic method could not adequately reflect the unpredictable characteristics of renewable resources and their influence on load fluctuations throughout the months. Thus resulted in unrealistic forecasts during months of February, July and December.

4. Conclusion

The application of a TCN-based BiGRU-LSTM model for forecasting monthly loads in HOMER establishes a solid foundation for time-series predictions, delivering more accurate projections of future energy requirements derived from past data. This contributes to the enhancement of energy system simulations and strategic planning. While HOMER serves as a robust instrument for modelling energy systems, it can yield discrepancies when projecting future energy demands based on monthly estimates. HOMER presumes uniform load patterns throughout the months, which cannot accurately represent the real fluctuations or irregularities identified by the forecasting model. The results showing renewable penetration for e.g., 26887.75%, point to possible discrepancies between the anticipated demand and the renewable generation statistics during certain months. This implies a necessity for a more refined approach to managing renewable energy variations within HOMER simulations to prevent overestimation. HOMER’s fixed methodology for forecasting load and generation constrains its ability to adapt to real-time fluctuations within energy systems. This could lead to less-than-ideal choices when strategizing for upcoming energy infrastructure, particularly in systems characterized by significant renewable integration and storage capabilities. While TCN-based BiGRU-LSTM predictions offer important insights into load trends, ongoing updates and adjustments to the projected load data are crucial for enhancing HOMER's simulation precision. Furthermore, incorporating variability, seasonality, and external influences could significantly boost the dependability of these forecasts. To address these limitations, the integration of real-time data with adaptive modelling techniques and the ongoing incorporation of feedback mechanisms derived from actual load and renewable energy performance can enhance the dependability of HOMER simulations, thereby ensuring that energy systems are configured more optimally for actual environmental conditions.

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