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# Forecasting Energy Demand with Deep Temporal Convolutional Networks in Smart Grid Applications

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**Abstract:** A grid is a power transmission system that interconnects power sources and distributes electricity to specific users through a high-voltage transmission approach and small-scale, low-voltage grid distribution. Energy demand forecasting involves predicting the electricity a particular user will consume based on electrical device usage and load demand, while avoiding impaired power connections due to overloading or under-processing of power systems. In previous work, challenges such as inaccurate or partial historical data, high error rates due to non-linear power supply, and increasing consumer demand on a day-by-day basis have been identified. To solve the problem, a Deep Temporal Convolutional Network (DTCN) is proposed for the Power Demand Forecasting approach in the Smart Grid application. DTCN is a deep learning architecture that captures temporal dependencies by preserving the input sequence and enabling parallel processing across time steps in each transmission. Forecasting energy demand helps grid operators identify periods of high consumption, optimizing power generation and distribution. The Simulation calculates RMSE parameters, including MAPE, which represents the percentage of absolute errors compared to the exact values. The Simulation achieves highly accurate forecasting using widely accessible deep learning procedures through open-source platforms.

**Keywords:** Forecasting Energy Demand; Load Demand; High-Voltage Transmission; Power Transmission System; Smart Grid Application; Open-Source Platforms; Power Demand Forecasting.

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## 1. Introduction

Forecasting energy demand is a key process in measuring potential energy consumption. Predicting future energy requirements uses historical data, weather (temperature) data, and energy consumption patterns. The selected model is trained on period-specific data and then validated through testing [1]. Accurate forecasting is crucial for strategic energy system planning. It reduces uncertainty and guides operational decisions across these systems, including future variable predictions. Historical data patterns are analysed using forecasting methods and operators of electrical grid systems; forecasting demand and generation is essential. The forecasting time horizon depends on the task: daily operations require short horizons, while grid planning and

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specific evaluations require longer horizons [2]. Electricity demand refers to the electrical energy that consumers, businesses, and manufacturing facilities use to meet their energy needs. Electricity demand is critical in energy management and development because it determines the generation, transmission, and distribution of electricity that must be provided to meet load demand. This training model uses a Modified War Strategy Optimization-Based Convolutional Neural Network (MWSO-CNN) to forecast power consumption. Both the state and the energy industry must accurately predict power demand and ensure a reliable, effective energy supply. However, previous projection methods often rely on mathematical approaches that identify complex relationships and patterns in data [3].

Accurate estimates of energy-use trends are vital for both sustainability and financial forecasting. Combining machine learning techniques and algorithms may improve prediction accuracy. This is especially important during this transition to continue supporting states and their economies as they work toward a cleaner, greener future. The weighted function and logistic regression were the most reliable methods for predicting standards in a dataset [4]. DNNs are used for predicting electric load, and it has been noted that DNNs can recognize complex temporal patterns in historical demand data, making them suitable for predicting electricity consumption. In the study, various deep learning methodologies were tested (e.g., RNNs, CNNs), and their accuracy was compared with that of more traditional methods. Real-time forecasting faces challenges in data scarcity and in obtaining a high-quality, labelled dataset. Additionally, the review suggested combining different machine learning methodologies in hybrid approaches to improve DNN accuracy and robustness [5]. Several methods can initiate demand forecasting when resources and data are limited. Another approach is to apply knowledge from other fields and analyze small datasets for different patterns, even in constrained environments. The results measured the use of combining external factors, such as economic data and domain-specific forecasting models. The potential of edge computing and other advanced forecasting approaches to improve forecasting algorithms with limited processing power [6].

### 1.1. Objective

- Designing a forecasting model for energy demand and reducing power losses in Peak-Hour Energy Consumption.
- Deep Temporal Convolutional Networks are proposed to enhance the precision of our weather forecasting models and reduce the false error rates.
- To improve reliability, resources must be evaluated to address the financial burden of original demand being too high relative to expected electricity demand.
- Accurate, timely energy demand forecasting is essential for reliable grid operation and reducing interruptions.
- Accurate load estimation is crucial to ensure a reliable supply of electrical energy that meets consumer demands and enables effective load control.

## 2. Previous Research Work

A key challenge for grid operators is maintaining energy balance to keep the grid stable. Operators must also continuously monitor and control power generation and load to improve efficiency. To optimize energy balance, operators often implement a Power Optimization Platform at the controller structure stage within the broader controller level. Annual planning occurs at the second level, accounting for seasonal fluctuations and setting the yearly manufacturing schedule based on demand and maintenance forecasts. Third-level production planning is then performed on a daily-to-weekly basis, and weather conditions, such as temperature, pressure, and wind speed, can significantly affect wind power output [7]. Predicting building energy use is a crucial part of digitally transforming the built environment while also seeking opportunities to reduce energy demand. Making building blocks resilient and flexible, while reducing energy use and maintaining occupant comfort, can diminish the impacts of climate change. Specific sensors enable us to monitor and manage building energy use by leveraging building optimization, event tracking, and user preferences. The output predicts peak demand and energy consumption for five different buildings using statistical, time-series, and machine-learning techniques [8]. Energy management technologies will increasingly be applied to implement and coordinate different energy sources in microgrid applications. However, uncertainty in renewable resource availability and energy output can be created and controlled, adding complexity to integrating energy management models into a microgrid system. Meanwhile, the particle swarm optimization method will be implemented to optimize each artificial neural network.

Furthermore, the system variables of multiple artificial neural networks will be related. The output outperforms more recent similar works, resulting in a 59% decrease in errors for both single-step and multiple-step prediction of energy parameter estimators [9]. Forecasting electrical energy use in homes within a smart grid is a crucial component for optimizing energy use and managing grid operation. The forecasted energy use patterns are designed to mitigate the risk of brownouts and oversupply, while enabling the use of dynamic pricing schemes that allow consumers to adapt to changes in supply and demand conditions. Accurate consumption forecasting will also support the seamless integration of renewable generation into the grid while balancing generation intermittency. Forecasting will also help utilities anticipate maintenance needs, enabling them to plan and build reliable systems while ensuring low-cost solutions [10]. A deep neural network, specifically an LSTM network, was

proposed as a short-term substitute for predicting power consumption because it can accept sequence and time-series data as input. We first applied the Coronavirus Optimization Algorithm (CVOA) metaheuristic and a random search to estimate the optimal values for a few hyperparameters. These hyperparameters included deep feedforward neural networks (grid search) and temporal fusion transformers (sampling algorithm). By contrast, traditional machine learning algorithms (decision trees, linear regression and tree-based ensemble algorithms (random forest and gradient-boosted trees)) were aggregated to minimize prediction error (usually less than 1-5% [11]).

Artificial Intelligence (AI) and energy optimization must transform how energy is generated, used, and distributed. AI, based on algorithms and predictive analytics, can assess energy consumption patterns in real time and identify adjustments to optimize consumption and meet demand. Smart systems can use energy consumption data to optimize use, improving sustainability and efficiency across multiple industries. Artificial intelligence (AI) may fully transform energy consumption monitoring systems. Energy monitoring systems are essential for reducing costs, minimizing environmental impact, and accurately tracking and effectively managing energy use [12]. Forecasting electrical consumption is important for planning and operating power systems. Various techniques have been employed to forecast electrical loads. Load forecasting is crucial for controlling and operating power systems, and it can save considerable time and reduce power losses. As a short-term electrical load predictor, researchers selected a feedforward neural network trained using backpropagation. The load-forecasting method is our trained and optimized neural network. We achieved these two measures through Simulation, and our neural network's prediction error was satisfactory [13]. As a fundamental human need, electricity is a pressing issue that any state must address to ensure its people have access to it and maintain a strong economy. Pricing, transmission planning, and generation capacity all depend on the ability to forecast power demand. Accurate demand forecasting allows power companies to make informed decisions about power system management and achieve significant cost savings.

Forecasting electricity consumption involves unique characteristics from various forecast viewpoints. For electric businesses, inaccurate forecasts can cause significant financial losses, as a 1% increase in forecasting error can increase power consumption [14]. Load forecasting is crucial for both utility and industrial companies, as it enables planning for future consumption and informs operational and strategic decisions. Very Short-Term Load Forecasting (VSTLF) supports online safety and operational analysis of power systems and electric utilities by predicting power consumption over the next few minutes to several hours. Short-term load forecasting (STLF) is equally important because it supports fuel allocation, fuel purchase scheduling, and economic dispatch. In power systems, STLF supports decisions on load switching and unit commitment [15]. The system's energy consumption characteristics and the interface relationship between the source and demand sides define the coupling link among the different loads in the combined energy structure. The integrated energy system's synergetic electric load forecasting model involves nonlinear synergetic relations among the loads due to coupling. The short-term electric demand forecasting model for the integrated energy system was built using support vector machines, BP neural networks, random forests, and gradient boosting decision-making algorithms. The IES-identified energy consumption characteristics and series-parallel relationships suggest that electric-conserving loads and heating loads are coupled and connected [16]. Predictive Home Energy Management Systems (HEMS) use the Relationship between Demand Response (DR) and a combined Bidirectional, Real-Time Pricing Mechanism (DBRTP) to optimize residential building energy consumption by integrating real-time pricing with prediction algorithms.

Consumers can adjust their energy consumption profile by setting energy costs based on current supply and demand. By applying bidirectional flow to DR offers and anticipating energy demand, users can systematically shift consumption to off-peak hours, improving grid performance and lowering costs. A comprehensive, reasonably priced HEMS provides the conditions needed for the sustainable use and storage of renewable energy sources [17]. The Economic Operation for Transactive Energy (TE)-Geographically Supported Multi-Energy Complementary Microgrids method focuses on the cost provisioning and energy flows of interconnected microgrids through economic transactions. This model operates within a market-based framework, enabling microgrids to exchange energy, heat, and electricity. Dynamic price signals enable producers and consumers to trade energy in real time at competitive prices, creating efficient gains for all parties involved. In addition, this model reduces reliance on the centralized grid and supports a distributed energy network, enabling lower-carbon, cheaper energy sources than the centralized grid by using localized supply chains. Energy independence is improved through reduced power loss, fewer complex errors, and a more sustainable energy mix by combining various energy sources [18]. Backpropagation Neural Networks (BPNNs) and Radial Basis Function Neural Networks (RBFNNs) are used in a two-stage approach to electric load forecasting. In stage two, RBFNNs are used to generate accurate forecasts. RBFNNs' ability to model nonlinear relationships is especially useful at this stage. Another capability is to add noise to the data, which effectively and meaningfully increases variability.

This variable, which introduces stacking noise, typically improves the model's ability to generalize and increases the number of training examples generated, as shown in [19]. Load forecasting is critical in the energy market, helping manage grid load and maintain supply-demand balance. The TCNN-GRU model captures spatiotemporal patterns in historical load data to provide reliable uncertainty quantification for both renewable energy and load demand. The ITLBO algorithm enhances

generation scheduling performance by using adaptive luminance coefficients. The H-CN method is also cost-effective: the TCNN-GRU model reduced solar irradiance forecasting RMSE by 11.6% relative to CNN-only estimates and reduced operational costs by 69.7% through ITLBO optimization [20]. Energy management in power systems is facilitated by the combination of a genetic algorithm-based Dynamic Economic Dispatch (GA-DED) approach, and the relevance of short-term load forecasting enables better precision in anticipating electricity loads, thereby enhancing overall decision-making capability in economic dispatch. Combining forecasting with GA-based optimization can improve energy supply and reduce emissions at lower cost and environmental impact, while improving grid integration of renewable energy sources with continuous reliability and reducing reliance on conventional fossil fuel-based generation [21]. An Automated Few-Shot Learning Approach for Time-Series Forecasting in Smart Grids under Data Scarcity enables the model to leverage knowledge from related tasks, allowing it to learn a task successfully despite limited data. This enables the model to make accurate predictions of energy demand, generation, and system performance even with limited data.

In summary, this process enables effective grid management and decision-making and improves performance stability when little data is available [22]. Linearly constrained estimators for short-term demand forecasting aim to improve forecast quality by combining or condensing multiple predictive models. The ensemble approach selects several estimators, assuming each has a benefit, to produce a more accurate forecast. The benefit of linearly constrained elite-level construction is that it ensures the action's nature conforms to certain operational or physical constraints. It also accounts for limitations in system stability or power generation. Furthermore, to reduce error and uncertainty in short-term demand estimates, the ensemble construction leverages multiple models [23]. Forecasts are used to predict supply availability and energy consumption, enabling better-informed decision-making. The peer-to-peer negotiation framework encourages consumers, generators, and storage systems to behave cooperatively. Because this method is decentralized, energy flows can adjust instantly in response to price cues and shifting conditions. As established by the distributed MPC dimension, it increases system resilience while ensuring local control actions remain consistent with the network's global constraints [24]. Demand-Side Management (DSM) for a Microgrid Based on Multi-Time-Scale Model Predictive Control (MPC) supports energy generation. It minimizes or controls microgrid energy loads by scheduling generation and consumption across multiple time scales. Derived from the MPC field, the method balances power supply and demand while forecasting and regulating energy flow over short-, medium-, and long-term periods. Both operational planning time scales and coordination efforts to manage the instantaneous energy balance will be aided by the combination of objectives across several time scales [25].

### 2.1. Problem Statement

In the above literature survey, forecasting of energy demand using different neural network algorithm techniques is reviewed, and each research work discusses forecasting with smart grid energy management and its limitations. Table 1 discusses the limitations of specific neural network approaches for energy demand forecasting, as measured by MSE, MAPE, and RMSE.

**Table 1:** Problem statement of different energy demand forecasting methods

| References | Algorithm and Outputs | Limitation |
|---|---|---|
| Fazle [26] | Gated Recurrent Unit (GRU) networks and MSE ≈50 | Long-term dependencies may not be managed effectively, requiring careful adjustments for different data types. |
| Priya [27] | Linear Regression algorithm and forecasting | Assuming a linear relationship may not suit complex, non-linear data. |
| Moayedi et al. [28] | MSE (4.4673), Earthworm Optimization Algorithm (EWA) | Parameter initialization can greatly affect performance and may increase computational costs. |
| Hieu and Lim [29] | Artificial Neural Network (ANN), Genetic Algorithm (GA), | Large datasets can cause GA to lag, while insufficient data may lead to overfitting or poor ANN performance. |
| Bilgili et al. [30] | Long Short-Term Memory (LSTM) and MAPE 1.91 %, RMSE 80.14 GWh | Training requires a significant amount of data, and extremely deep networks risk vanishing gradients. |

## 3. Materials and Methods

Forecasting energy demand is crucial to this work. We perform specific calculations step by step as part of the data preparation process before the model runs any time-series metrics or models. To identify factors related to the target variable, various statistical measures can be used. While correlation can be used, more sophisticated measures such as Recursive Feature Elimination (RFE) may also be employed. Selecting the right features is crucial for accurate energy demand forecasting. When using a DTCN, consider time-series data and predict future customer behaviour based on past patterns. The model output can improve forecast accuracy, provide valuable insights, and highlight areas that may require further consideration or improvement. In Figure 1, the first stage involves collecting all relevant customer behaviour and weather data from a specific

source. In the proposed work, data transformations are based on what is considered "raw"; thus, cleaning and transformations occur to ensure accuracy through mathematical analysis. Feature selection identifies the features (or variables) in the dataset most relevant to the analysis and predictive modelling use case. The DTCN, a deep learning model well suited to time series forecasting, forms the foundation of this work. An effective way to show the average size of the error between the expected and actual values is to use RMSE, and the prediction accuracy is displayed as a percentage by MAPE.

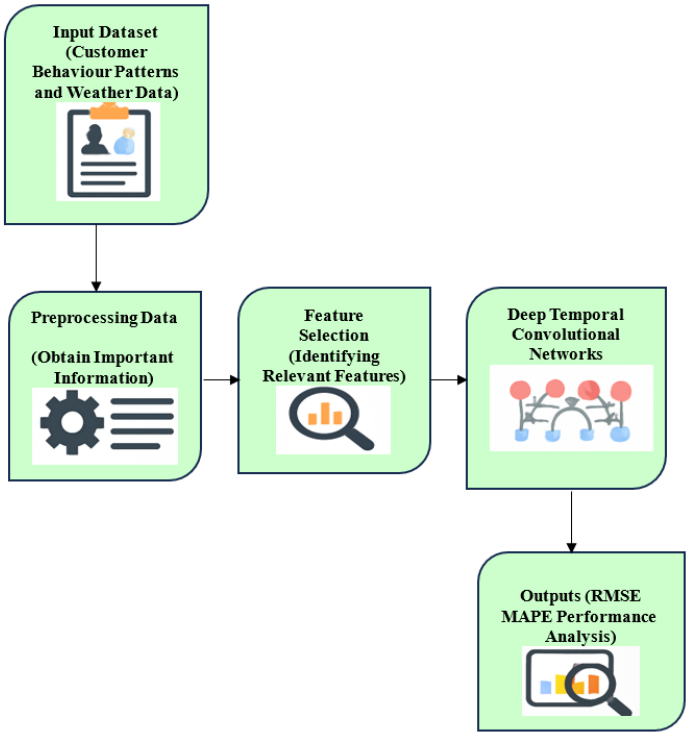



**Figure 1:** Block diagram of proposed forecasting energy demand using DTCN

### 3.1. Input Dataset (Customer Behaviour Patterns and Weather Data)

The input dataset for forecasting energy demand consists primarily of two components: customer behaviour patterns and weather data. Customer behaviour patterns include historical usage data and demographic information, used to assess consumption and inform demand forecasts.

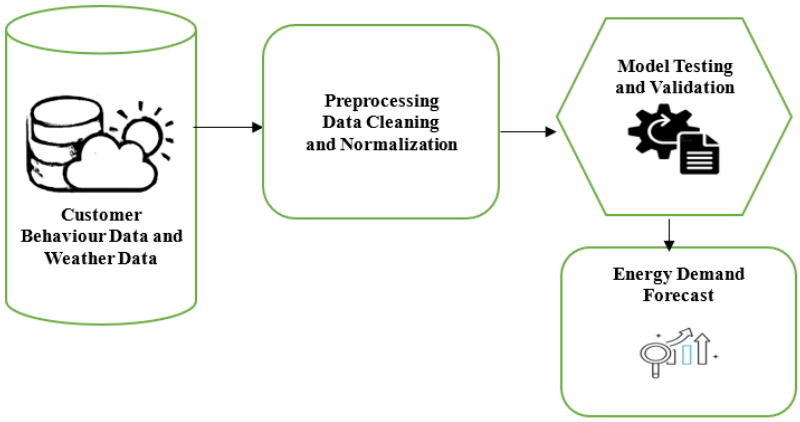



**Figure 2:** Working with data preprocessing

Weather data captures environmental measures of socio-physical influences, including temperature, that affect energy consumption. Weather patterns will change, affecting energy consumption levels and ultimately correcting demand forecasts.

In many scenarios, weather shapes consumption behaviours, especially around heating and cooling, and influences energy-demand forecasts. In Figure 2, the convergence of customer patterns, weather inputs, and machine learning enables energy providers to predict short- and long-term energy requirements accurately, ensuring supply and demand can be matched and proposed facilities can be sized accurately. Input datasets in energy forecasting are crucial for developing a suitable machine learning model and creating the data-driven forecasts needed for the future. These two data sources enable a more comprehensive understanding of forecasting and support energy learning by considering customer behaviours and extraction within a service area that can offset energy use. These two data sources support decision-making on energy optimization and source action plans during sector supply difficulties.

### 3.2. Data Preprocessing: Forecasting Energy Demand

Data preprocessing should prepare raw data for subsequent model training through cleaning, transforming, and formatting within a systematic framework. In the energy demand forecasting space, common preprocessing steps include outlier detection, feature extraction, Normalization, and handling missing data when variables have different scales (for example, energy consumption is frequently measured in kilowatts, but time intervals could be measured in either hours or days):

$$Y_t = \alpha Y_t + (1 - \alpha) Y_{t-1} \quad (1)$$

In equation (1), Y_{t} is evaluated as a missing data point, \left(1-\ \alpha,\ \right)\ different-stage forecasting preprocessing phase. There are several ways to fill in missing data, such as using imputation methods or replacing missing values with the mean or median; additionally, subsequent features still need to be completed. In preparing data well at the preprocessing stage, it should be reliable and structured correctly to minimize noise and enable efficient learning by the model:

$$y_t = T_t + S_t + E_t \quad (2)$$

In equation (2), data quality, generalization and the model's forecasting capacity are crucial for designing the data preprocessing stage to improve predictive ability. Here, y_{t\ }represents the actual energy demand, {\mathrm{T}}_{\mathrm{t}} is missing value. In Figure 2, data preprocessing scales each data point to a predefined interval. Time-based and Statistical features, commonly used in energy forecasting preprocessing, can be useful (Figure 3).

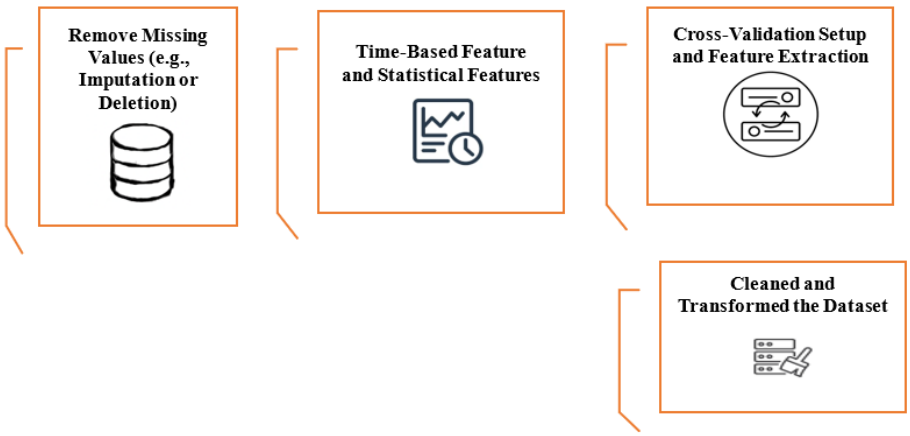



**Figure 3:** Working with data preprocessing

### 3.3. Feature Selection

Feature selection identifies input variables (features) that can be used in predictive models without loss from a curated set of available data. For energy demand forecasting in smart grids, feature selection involves choosing input variables that correlate with energy consumption; for example, to stress-test predictive models, consider weather data, time-of-day data, previous load data or patterns, and socio-economic factors that could change load behaviours. Feature selection is essential to the development of all types of smart grids, as it enables the prediction of energy demand while struggling with the restraints of the complex datasets created by the operation of all smart grids, which involve millions of resources with varying time, duration, and types:

$$I(x,y) = \sum_{x \in X} \sum_{y \in Y} p\ (x,y) \log \left( \frac{p(x,y)}{p(x),p(y)} \right) \quad (3)$$

In equation (3), smart grids collect data I(x, y) from a specific model, and p(x, y) are Distributed Energy Resources (DERs) to facilitate better demand management, processing loads of data points per minute. Identifying the factors that impact demand in these repetitive smart-grid datasets can be extremely complex, and feature selection helps smart-grid applications narrow down the relevant factors (Figure 4).

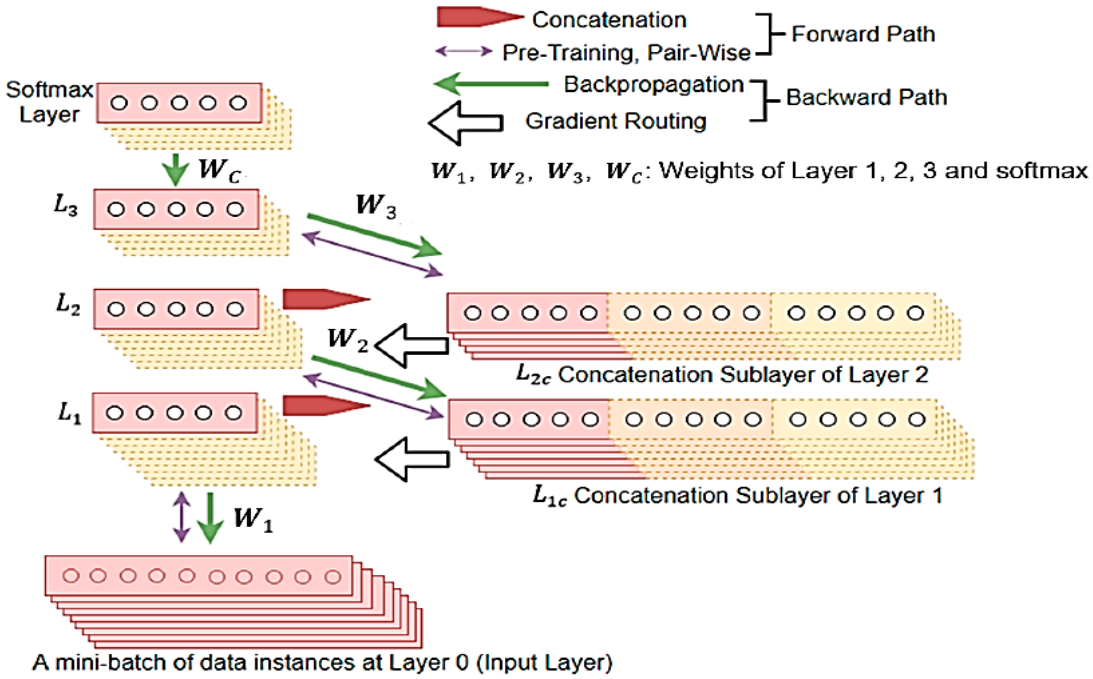



**Figure 4:** Working architecture of deep temporal convolutional networks

Correlation analysis, mutual information analysis, and machine learning techniques (recursive feature elimination and regularized forecast predictors) are commonly used. Using appropriate feature selection techniques can improve forecasts, optimize consumption, and inform demand-side management and energy distribution decisions. Deep TCNs are a deep learning architecture specifically designed to process sequential data. They are trained on historical trajectory data and can predict future paths for Energy Demand Forecasting. An interacting approach for modelling temporal dependencies in path prediction tasks, capturing short-term and long-term dynamics efficiently and with interpretable receptive fields. Activation functions and pooling layers follow, down-sampling the dimensionality from the convolutional layers.

Gradient Routing and Pre-training: Figure 3 assesses pre-training and gradient routing as learning mechanisms used by models. Gradient routing optimizes a model through gradient-based updates. Pre-training (for example, pairwise) primes a network for better performance before the main training period. The time and space in which data is collected, the spatiotemporal context, shape the data. This is because each time-series data point has neighbouring points close in time. In a typical example of DTCN (define this term or use a more descriptive phrase), the input time-series data undergoes multiple convolutions. The network architecture can be expressed as follows in equation (4). This allows the model to adjust the weights W1, W2, W3, and Wc to minimize error and improve performance. It is essential to provide context and background information to fully understand the purpose and function of the model and data:

$$Y_t = f\,(W * X_{t-n:t} + b) \tag{4}$$

$Y_t$ is a predictive forecasting model, $X_{t-n:t}$ b. The time step includes a value, and W is the Weighted bias:

$$Z_t = k = 0k - 1wk.xt - k + b \tag{5}$$

In equation (5), $Z_t$ is the convolutional time output, and K is the size of the convolutional layer. In DTCN, the convolution operation is designed to handle sequential data. The convolution operation learns a set of filters that capture temporal dependencies in a time series. This has the following mathematical definition:

$$MSE = \frac{1}{n} \sum_{t=1}^{n} (Y_t - Y_t^{actual})^2 \tag{6}$$

In equation (6), Residual connections, also known as skip connections, are added between layers to reduce the vanishing gradient issue and increase training effectiveness:

$$y_t^{res} = f\ (x_t) + x_t) \quad (7)$$

In equation (7), f ($x_t$) characterizes the output from the difficult process; $x_t$ is an input from the previous layer, $W_1$:

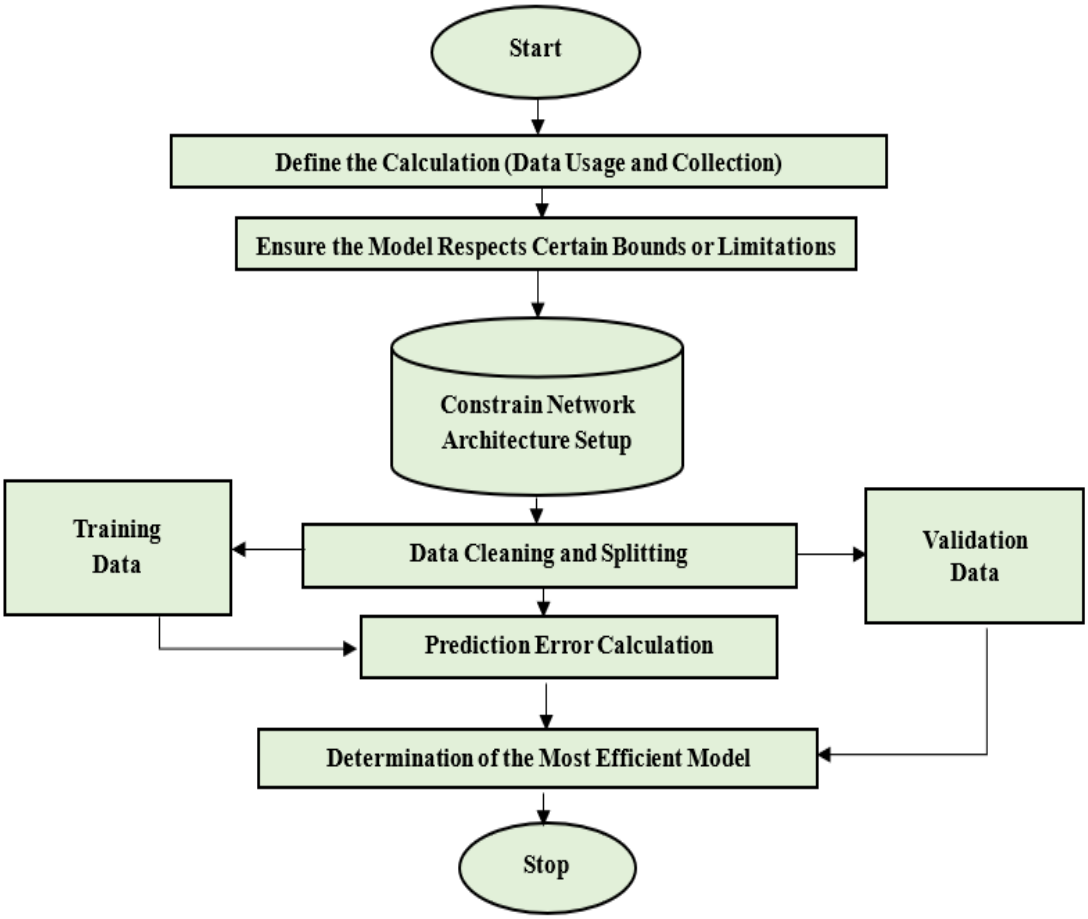



**Figure 5:** Flow chart of proposed DTCN using forecasting energy demand

Figure 5 shows the flowchart for using DTCN in the Energy Optimization System, which begins by defining the data and ensuring it includes Customer behaviour patterns and weather data. Next, the data is divided into two sections: the validation dataset and the training dataset. If the training and testing minimize error, subsequent iterations are carried out to adjust the network architecture by limiting certain factors. The process evaluation and validation are finally conducted to ensure that the model's estimates meet the desired specifications before concluding the process.

## 4. Results and Discussions

Forecasting energy demand plays a crucial role in our grid stability calculations, using the DTCN model with adjusted parameters to enhance power quality. To generate accurate efficiency predictions, we need substantial smart grid power-usage data. Therefore, researchers used real-time smart grid data for predictions. To ensure model accuracy, we compared the models against a validation dataset. We compared each model's predictions and calculated the Mean Absolute Error (MAE) for each.

### 4.1. Data Upload of Forecasting Energy Demand in Smart Grid

Figure 6 shows the total load prediction and demonstrates the DTCN model's comparative performance in forecasting energy demand.

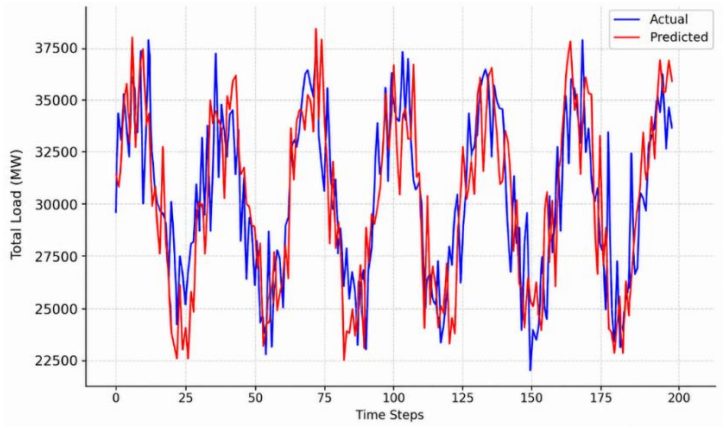



**Figure 6:** Total load prediction

Figure 7 shows an artificial energy consumption timeline, featuring seasonal patterns represented by oscillations. First, it captures predictable periodic variations with a sinusoidal base function and adds random noise to reflect the random aspects of energy consumption.

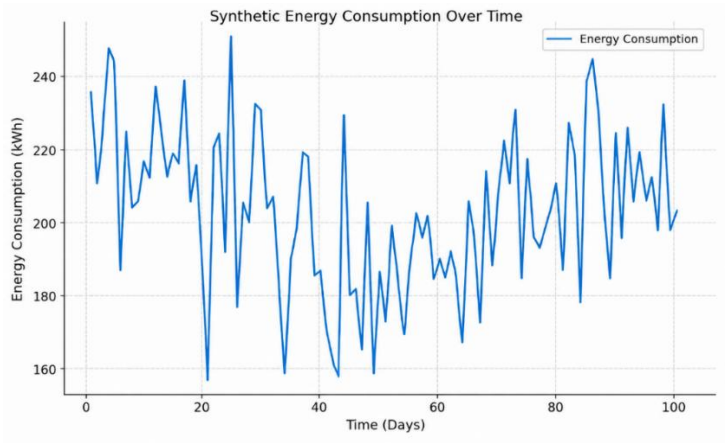



**Figure 7:** Synthetic time-series for (Consumer Behaviour Patterns and Weather Data)

The transformed energy consumption series is used to forecast and optimize energy systems. Figure 8 shows actual energy demand (MW) over 100 time steps (simulating days), with added random noise to reflect variations in actual energy consumption; the demand appears to follow a seasonal pattern.

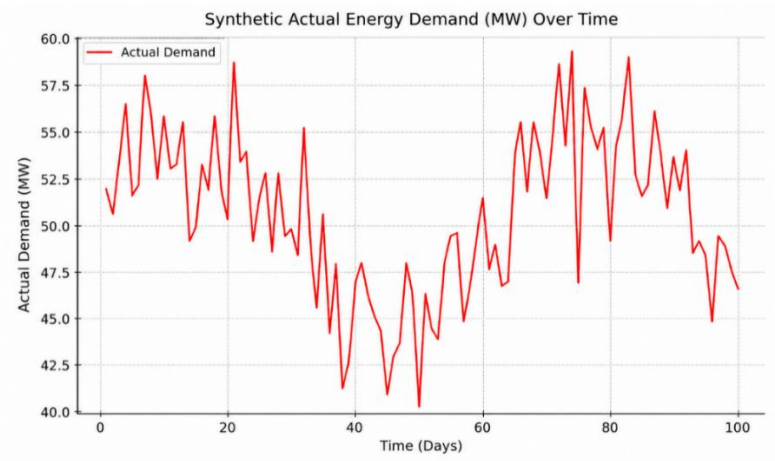



**Figure 8:** Synthetic actual energy demand

In an energy demand forecasting model, Table 2 shows realistic values for the day, hour, and month performance. Standard statistical measures, including count, mean, standard deviation (SD), and percentiles (25th, 50th, and 75th), are presented across periods.

**Table 2:** Predictors description of the dataset

| Data Descriptor | Day | Hour | Month |
|---|---|---|---|
| Count | 10000 | 10000 | 10000 |
| Mean | 20 | 14 | 9 |
| SD | 10 | 8 | 3 |
| Min. | 0 | 0 | 4 |
| 25% | 12 | 8 | 6 |
| 50% | 20 | 14 | 9 |
| 75% | 28 | 20 | 12 |
| Max. | 50 | 24 | 16 |

### 4.2. Performance Evaluation Metrics

The model was evaluated on the mean absolute error (MAE) and Root Mean Square Error (RMSE), based on the MAE, which can measure (i) the Magnitude of predictions and (ii) the Dimension of error, as shown in equations 8 to 10. An example of MAE is the average absolute difference across the entire testing dataset between the actual value and the predicted value:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(L_i - \bar{L}_i)^2}{\sum_{i=1}^{N}(L_i - \bar{L}_i)^2} \quad (8)$$

$$RSME = \sqrt{\frac{1}{2}\sum_{i=1}^{N}(L_i - \bar{L}_i)^2} \quad (9)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}(L_i - \bar{L}_i)^2 \quad (10)$$

**Table 3:** DTCN performance evaluation with various neuronal counts

| Sample | Training | Validation | Testing | All |
|---|---|---|---|---|
| R-square (10) | 0.90532 | 0.91254 | 0.89743 | 0.90112 |
| MSE (10) | 0.0042158 | 0.0043257 | 0.0037632 | 0.0041345 |
| R-square (20) | 0.91483 | 0.91832 | 0.91192 | 0.91369 |
| MSE (20) | 0.0039812 | 0.0038741 | 0.0035617 | 0.0038054 |
| R-square (30) | 0.92756 | 0.92163 | 0.92048 | 0.92313 |
| MSE (30) | 0.0031741 | 0.0033892 | 0.0034928 | 0.0033454 |
| R-square (40) | 0.93417 | 0.93654 | 0.92843 | 0.93371 |
| MSE (40) | 0.0027985 | 0.0025338 | 0.0031024 | 0.0028116 |
| R-square (50) | 0.94572 | 0.94813 | 0.93791 | 0.94165 |
| MSE (50) | 0.0022317 | 0.0026018 | 0.0028623 | 0.0025653 |

Table 3 reports R-squared and MSE, two performance metrics that demonstrate the method's efficiency and reliability across the evaluation stages. All differences are weighted equally when calculating MAE. In Table 4, the RMSE measures the standard deviation of errors in both the training and testing sets. MSE is also a statistical measure that characterizes the average difference between actual observations and predictions in both the training and testing stages.

**Table 4:** Result comparison of the proposed DTCN

| Model | MAE (Testing) | MAE (Training) | RMSE (Training) | RMSE (Testing) |
|---|---|---|---|---|
| DTCN | 0.00290 | 0.00235 | 0.00345 | 0.00412 |
| LSTM | 0.00350 | 0.00300 | 0.00410 | 0.00460 |
| GRU | 0.00320 | 0.00280 | 0.00390 | 0.00450 |
| ANN | 0.00450 | 0.00400 | 0.00520 | 0.00580 |

Figure 9 compares DTCN performance with previous methods, such as CNN, TCN, and DTCN, using metrics like RMSE and MAE on both the training and testing datasets. The results show that DTCN improves energy demand forecasting accuracy.

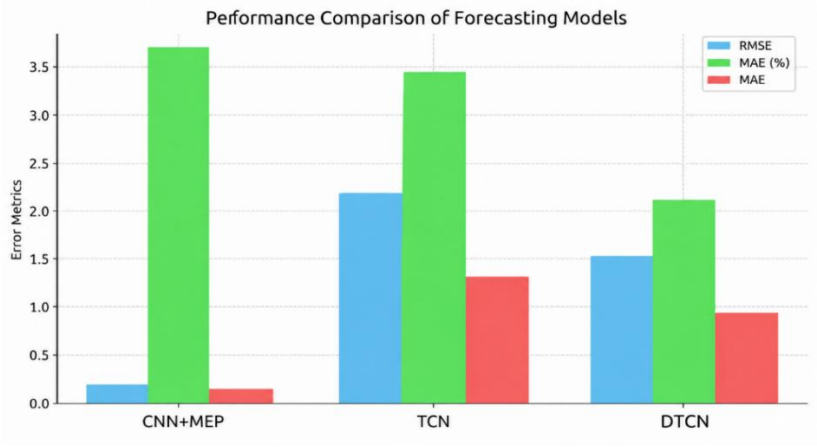



**Figure 9:** Comparison analysis of forecasting energy demand

## 5. Conclusion and Future Scope

Energy consumption prediction for forecasting energy demand for smart grid applications through DTCN is analysed in this work. The DTCN model captures sequential patterns in energy consumption data and is compared with LSTM and GRU, as shown by improved accuracy metrics. The DTCN model also outperforms LSTM and GRU, with the following accuracy statistics: RMSE (training) = 0.00345, RMSE (testing) = 0.00412, MSE (training) = 0.0041345, and MSE (testing) = 0.0042158. The results indicate that DTCN has potential for forecasting energy demand, a key capability that improves grid processes and load management in constant-power systems. This work aims to develop innovative grid technology and utilize state-of-the-art deep learning methods to address the current and future energy demands of diverse consumers. The output of the model selection and optimization strategies is an accurate and dependable predictive model. In the future, research could include combining hybrid models that apply advanced neural networks and other support vector or random forest types of machine learning, which could be used to improve forecasting and also smart grid management. Also, applying advanced neural network architectures to existing infrastructure for forecasting transferable grids would benefit energy providers by enabling them to accurately model short-term energy requirements and make informed, rapid decisions in real time. Furthermore, this research could explore using data from other innovative city systems, such as transportation, water management, and social or health care, to build a comprehensive dataset for energy demand prediction and management.

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