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A Comparison of State-of-the-Art Time Series Classification for Demand Estimation in Prosumers

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Abstract:
Renewable energy, particularly solar photovoltaic systems, is essential for a sustainable future. This article explores the role of distributed generation systems, smart grid technologies, and demand-side management in integrating renewables into the grid. Demand-side strategies, such as demand modeling, improve grid stability, reduce costs, and minimize environmental impact. This study uses a residential energy consumption dataset to compare deep learning models for electrical demand forecasting, including Fully Convolutional Networks, Residual Networks, Long Short-Term Memory, and Time Series Transformers. The results show that Residual Networks achieved the highest R^2 score (0.939). This highlights the potential of advanced machine learning for efficient energy management and forecasting.

***Keyword**: Smart Grid; Renewable Energy; Artificial Intelligence; Demand-Side Management; Prosumers.*

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I. Introduction

According to the International Energy Agency (IEA), renewable energy sources represent the most promising energy matrices for widespread adoption in the coming years. In 2023, the global renewable energy capacity reached an estimated 507 GW, almost 50% more than in 2022. This remarkable growth has been driven by the sustained support of policies in more than 130 countries, which fosters a significant shift in global growth trends [1]. Solar photovoltaic (PV) has the highest growth potential among all renewable energy sources worldwide. This is mainly because consumer adoption can accelerate once economics become more favorable [1].

Considering that solar PV systems are among the easiest and simplest technologies to install for low-voltage consumers, their adoption is expected to increase proportionally as the technology becomes more affordable [2]. With the implementation of distributed generation systems, which can operate on-grid, energy generated by PV systems can be stored in batteries, used for local consumption, sent to the distribution grid as surplus, or drawn from the grid in cases of insufficient generation. The integration of these systems is further supported by smart grid technologies, which allow for better coordination and efficiency in managing energy flow, storage, and consumption.

When addressing the electricity demand of residential consumers, demand-side management is an essential factor for distributed generation systems since it can optimize energy usage and ensure efficiency. Demand-side management (DSM) encompasses strategies and practices aimed at managing and optimizing energy consumption by end-users. Its primary goals are improving energy efficiency, reducing costs, and contributing to the stability and sustainability of the electrical grid.

DSM enables consumers to monitor their energy usage during peak demand events. This continuous monitoring and management enhance system reliability and reduce energy costs [3]. According to [4], DSM is a vital tool for addressing climate change and achieving carbon neutrality, making it indispensable for overcoming the current challenges in the energy sector. DSM plays a significant role in managing distributed energy resources, renewable energy sources, and storage devices, ensuring the overall efficiency of the system [3]. The applied techniques may include responsive loads, ripple control, price incentives, or time-of-use tariffs. Moreover, end-users gain greater control over local energy supply and usage through on-site generation, such as rooftop solar panels, electric vehicles, and smart technologies for load management [5]. Thus, DSM facilitates the effective integration of renewable energy sources and minimizes environmental impacts [6].

Key applications of DSM for reducing electricity consumption include [4]: demand modeling and load forecasting [7], consumer behavioral analysis, demand response programs, smart technologies, and grid stability contributions [8]. One innovative approach to analyzing electrical demand within DSM is using artificial neural network models for time-series analysis, offering insights to optimize energy usage patterns and enhancing system efficiency.

There are several neural network models for performing time series regression, such as Convolutional Networks, Residual Networks (ResNet), Long Short-Term Memory (LSTM), and Time Series Transformer (TST). Recent studies on short-term load forecasting in microgrids, such as the works by Moradzadeh et al. (2020) [9], Guimarães et al. (2020) [10], and Muzumdar et al. (2022) [11], have explored various machine learning techniques like SVR, LSTM, and hybrid models to improve prediction accuracy. However, these studies often lack a comprehensive comparison of state-of-the-art deep learning methods for time- series forecasting in the context of energy consumption as distributed generation on grid consumers.

Our article aims to utilize time series classification models to evaluate the accuracy of a regressor for the electrical demand of a house equipped with a grid-connected PV module. The models employed are LSTM, ResNet, Fully Convolutional Network (FCN), and TST. The main contribution of the article includes:

- Comparison of deep learning models for energy demand forecasting;
- Identification of ResNet as the best-performing model;
- Application of DSM techniques for energy optimization;
- Utilization of real-world datasets for model validation;
- Suggestion for future research on deep learning integration in DSM.

The remainder of this paper is arranged as follows. Section II lists related work. Section III describes the methodology used to train and predict the demand. Section IV discusses the results of the experiments. Finally, Section V, Conclusion, summarizes the findings and suggests future research.

II. Methodology

The data used in this work are from Trivedi et al. (2024) [12], which developed an energy-related dataset from residential electricity usage in an energy community in Ireland. It includes local weather parameters and minute-by- minute household data on power (W) and energy (Wh) components, covering active power consumption, PV generation, grid import/export, and energy storage charging/discharging. In this work, active power consumption, PV generation, grid import and export, and charging and discharging were used. As shown in Figure 1, the flowchart illustrates the process of data manipulation, transformation, and modeling for energy consumption using deep learning.

The original data were manipulated to remove the impact of battery charging on electrical consumption, with only 1440 minutes (24 hours) used. The input variables X include PV generation, grid import/export, and storage charging/discharging, while the output (y) represents active power consumption. The data were transformed into fixed-length sliding windows (60 steps) and organized into the format required for time-series-based models. After splitting into training and validation sets, regression, normalization, and training transformations were applied using different state-of-the-art time series regression architectures, which are detailed below.

The Fully Convolutional Network (FCN) is an architecture composed exclusively of convolutional layers, without including dense layers, which allows it to process inputs of varying sizes. Widely used in segmentation tasks and time series analysis, the FCN effectively captures local patterns in the data, such as trends and cycles. The absence of dense layers reduces the number of parameters and enhances the model's generalization, making it lightweight and efficient. Its ability to operate directly on raw time series data makes it a popular choice for applications such as event classification and prediction [13].

The ResNet is a deep neural network architecture based on residual connections, which allow raw information to "skip" across multiple layers. This mitigates the vanishing gradient problem in deep networks, facilitating learning in complex models. The ResNet consists of residual blocks that include convolutional and nonlinear layers, making it highly effective in learning hierarchical representations of data. It is ideal for computer vision and detecting complex patterns applications [13].

The TST applies concepts from Transformers, originally developed for natural language processing, to the domain of time series. It uses attention mechanisms to efficiently capture global dependencies in the data without relying on sliding windows or strictly ordered sequences. The TST is particularly powerful for modeling long-range relationships in temporal data, making it suitable for forecasting, anomaly detection, and behavioral analysis in complex time series [14].

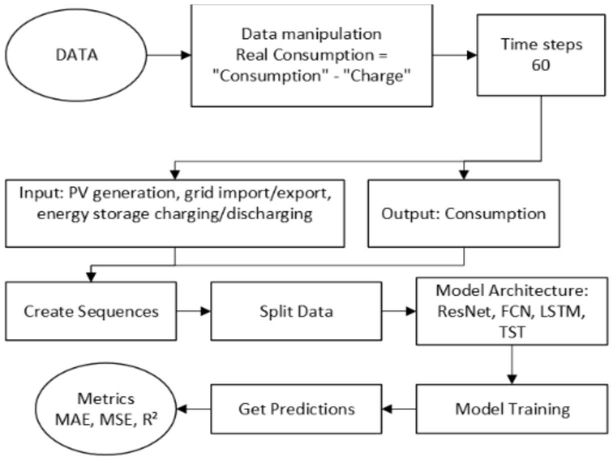

Figure 1. Overview of the proposed method.

The LSTM is a special type of recurrent neural network (RNN) designed to model long-term dependencies in sequences. It excels due to its memory cells, which can store and manipulate information across multiple time steps, allowing it to capture complex temporal patterns. Unlike traditional RNNs, LSTMs avoid the vanishing gradient problem by using mechanisms such as input, output, and forget gates. As a result, they are widely used in tasks such as time series forecasting, natural language processing, and sequential pattern recognition [15].

Subsequently, the trained models were evaluated using metrics such as coefficient of determination (R^2), mean absolute error (MAE) and mean squared error (MSE), exported in ".pkl" format, and used for inference with both visual and quantitative validation. A more detailed explanation of the methodology is presented as follows.

The script uses the TSAI [16] library in Python and the file "H10_Wh.csv". From these data, the electrical consumption is first manipulated, as the battery charge is considered to be part of the consumption, which is not desirable when combined with the electrical demand. Therefore, the "charge" column is subtracted from the "consumption" column. For this study, data were used for up to 1440 minutes, i.e., 24 hours, similar to [17].

The input data X consists of PV generation, grid import/export, and energy storage charging/discharging. The output data (y) are the active power consumption. Subsequently, the data are transformed into sequences to be used as input for deep learning-based models. A function is defined to create sliding windows of fixed length (n_steps = 60), extracting the features (X) and target (y) in a time-aligned manner. After transformation, the sequences are organized in the format required by the models (number of samples, number of channels, sequence length) and converted to the "float32" data type.

The data are then split into training and validation sets using the "get_splits" function, ensuring that a portion of the data is set aside for model performance evaluation. The code uses the "TSRegressor" class to train models based on different architectures, including TST, FCN, LSTM, and ResNet. Specific transformations for regression are applied to the data using "TSRegression". The data are standardized with "TSStandardize".

The model is trained using the "fit_one_cycle" method for n-epochs, with an initial learning rate of 0.0003. The trained model is exported for future use in ".pkl" format. After training, the model is loaded using "load_learner" to perform inference on the validation data. The actual values (target) and predicted values (predictions) are plotted in a graph for visual analysis. Additionally, performance metrics such as R^2, mean absolute error (MAE) and mean squared error (MSE) are calculated to evaluate the model quantitatively.

III. Results and Discussions

The models are tested as follows. For ResNet, the following kernel sizes were used in three blocks: 7, 5, and 3. The first block used 64 filters, while the second and third blocks used 128. The training difference is the number of epochs: ResNet A: 100 epochs; ResNet B: 500 epochs; ResNet C: 1000 epochs.

For FCN, the best configuration found was: Layers 256, 256, 256 with kernel sizes 9, 7, and 5, for 100 epochs with Adam optimizer. For LSTM, the best configuration was: Hidden size 200, 5 layers, RNN dropout 0, Bidirectional True, fully connected dropout 0, for 500 epochs with Adam optimizer (learning rate: 3e-4).

For TST, the best configurations tested were: TST A: 3 layers, model dimensionality 128, number of attention heads 16, dimension of feed-forward network 256, dropout 0.1, fully connected dropout 0, activation function: gaussian error linear units (GELU), for 100 epochs with Adam optimizer (learning rate: 3e-4); TST B: 2 layers, model dimensionality 128, number of attention heads 32, dimension of feed-forward network 512, dropout 0.2, fully connected dropout 0.2, activation function: GELU, for 100 epochs with Adam optimizer (learning rate: 3e-4).

The predictions of the models and their accuracy are shown in Table no 1. The best R^2, MSE, and RMSE were achieved by the ResNet model with 500 epochs and an Adam optimizer (learning rate: 3e-4). As shown in Figure 2, it demonstrates strong regression performance.

Table no 1: General model results

Model	*R²*	*MAE*	*MSE*
ResNet B	0.939	3.128	54.232
TST A	0.934	4.88	64.382
TST B	0.934	4.705	56.469
ResNet C	0.927	2.913	42.602
ResNet A	0.914	3.867	42.706
FCN	0.891	4.569	70.057
LSTM	0.862	2.93	110.176

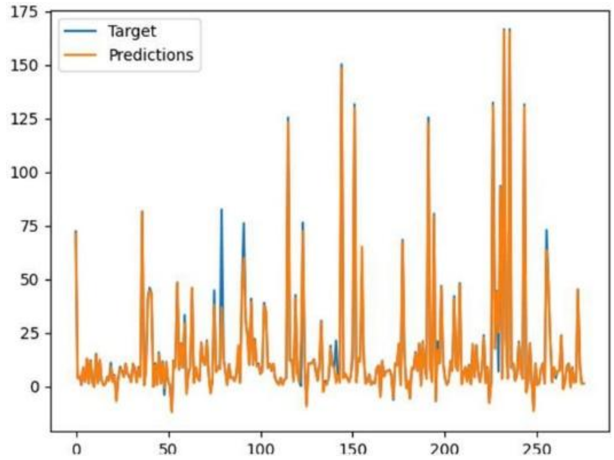

Figure 2. Visual Results for the REsNet B model.

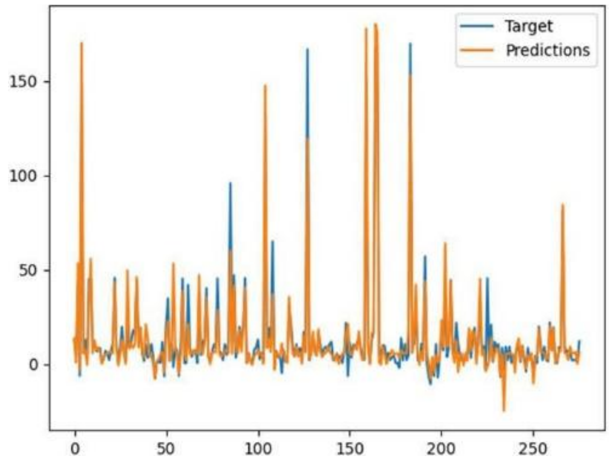

Figure 3. Visual Results for the TST A model.

TST also demonstrated strong performance, presenting a viable alternative to ResNet A. The TST A model achieved an R^2 of 0.834, as shown in Figure 3, only slightly lower than the best-performing ResNet model. This suggests that Transformers can be highly effective, particularly for tasks involving sequences or temporal dependencies.

The performance variation observed between TST models with two and three layers, as well as differences in the number of heads and feed-forward units, highlights the significant influence of architecture on outcomes. The TST model with three layers and 128 units outperformed configurations with only two layers.

Additionally, models trained for more epochs tend to deliver better results, as evidenced by the ResNet trained for 500 epochs, which outperformed its 100-epoch counterpart. The inclusion of dropout in specific TST configurations did not yield dramatic differences in results but may serve as a crucial technique to mitigate overfitting, particularly with more complex datasets. Conversely, LSTM models performed worse compared to both ResNet and TST, particularly in terms of R^2 and MSE. Bidirectional LSTMs with increased layers and units showed minimal improvement, as shown in Figure 4, suggesting that for this specific task, LSTM models may not be as effective as CNN-based models like FCN, as shown in Figure 5, or TST. Overall, both ResNet and TST are good choices for use in electrical demand regression.

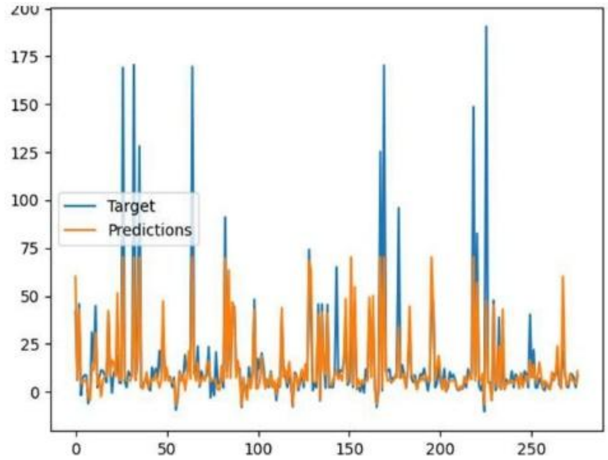

Figure 4. Visual Results for the LSTM model.

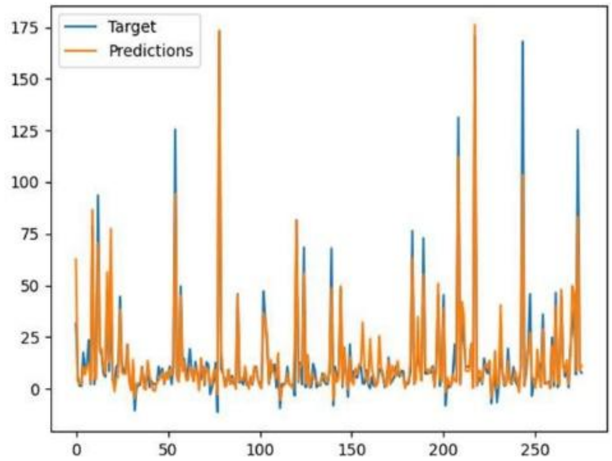

Figure 5. Visual Results for the FCN model.

IV. Conclusion

Smart grids represent a fundamental transformation in electric power systems, offering significant benefits in terms of efficiency, sustainability, and resilience. The integration of advanced communication technologies, combined with the application of AI techniques, plays a crucial role in the optimization, automation, and dynamic control of these networks. The vast amount of data generated by the different components of the grid paves the way for AI to be applied to a wide range of functions, from load forecasting to predictive maintenance and cybersecurity.

Adopting renewable energy sources, particularly PV systems, represents a pivotal step towards sustainable energy solutions. The growing global capacity for renewable energy and advancements in distributed generation systems are reshaping the energy landscape. DSM is critical in optimizing energy use, improving grid stability, and effectively integrating renewable sources.

In the context of predicting electrical demand, deep learning models offer promising avenues for improving energy forecasting and resource allocation. The results of this study highlight the superior performance of ResNet and TST models for time-series regression tasks in the energy domain.

Both models exhibit high accuracy and robustness, with ResNet demonstrating the best overall performance, while TST models show significant potential as an alternative, especially for handling complex temporal dependencies. Conversely, LSTM models, despite their design for sequence data, lagged behind due to their limitations in capturing the intricate patterns of this dataset.

The findings underscore the importance of model architecture and training strategies in achieving accurate demand predictions. Future research could explore hybrid approaches combining the strengths of CNNs, Transformers, and other techniques to enhance performance. Additionally, extending forecasting to longer periods could provide valuable insights into seasonal trends and help improve the robustness of demand-side management strategies. By leveraging advanced machine learning methods, integrating renewable energy sources can be optimized, contributing to a more efficient, reliable, and sustainable energy future.

V. Acknowledgment

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