A DEEP LEARNING APPROACH TO ENERGY DISAGGREGATION USING TCN LAYERS FOR APPLIANCE AND LOAD INSIGHTS

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Abstract:

Non-Intrusive Load Monitoring (NILM) plays a vital role in energy efficiency by disaggregating appliance-level consumption from aggregated household energy data. A conventional Temporal Convolutional Networks (TCNs) doesn't have classification and regression sub-networks. This study explores the use of TCNs for parallel appliance classification and load prediction, addressing challenges like overlapping energy signatures and long-term temporal dependencies. The TCNs, with their dilated causal convolutions and efficient parallel processing, are well-suited for NILM applications, offering improved scalability and accuracy over traditional machine learning and recurrent neural network (RNN) approaches. The proposed framework utilizes multi-task learning to classify active appliances and predict their energy consumption simultaneously, reducing computational overhead and enhancing system adaptability. Experiments on publicly available datasets REDD, UK-DALE, demonstrate the TCN model's superior performance, achieving higher classification accuracy, improved load prediction fidelity, and robustness under noisy conditions. The lightweight and scalable architecture ensures suitability for real-world deployment, including smart grid systems and residential monitoring.

Acronyms

Acronym	Full form
NILM	: Non-Intrusive Load Monitoring
TCNs	: Temporal Convolutional Networks
RNN	: Recurrent Neural Network
HMMs	: Hidden Markov Models
LSTM	: long short-term memory
DBB-TCN	: Double-Branch Bi-Directional Temporal Convolution Network
GRUs	: gated recurrent units

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DNNs	: Deep Neural Networks
SVM	: Support Vector Machines
k-NN	: k-Nearest Neighbours
GAN	: Generative Adversarial Network
DAE	: Denoising Autoencoder
SGN	: Subtask Gated Network
REDD	: Reference Energy Disaggregation Data Set
MSE	: Mean Squared Error
MAE	: Mean Absolute Error
SAE	: Signal Aggregation Error

Highlights

- The study leverages TCNs for energy disaggregation, effectively handling long-term temporal dependencies and overlapping energy signatures.
- The proposed approach simultaneously classifies active appliances and predicts their energy consumption, improving computational efficiency and adaptability.
- Experiments on REDD and UK-DALE demonstrate that the TCN model outperforms traditional methods with lower MAE and SAE and higher F1-scores.
- The lightweight architecture ensures robustness under noisy conditions, making it suitable for smart grid applications and residential energy monitoring.

1 Introduction

Non-Intrusive Load Monitoring has emerged as a key method for enhancing energy efficiency in residential and commercial settings by disaggregating aggregate electrical consumption into individual appliance-level profiles [1]-[3]. Unlike traditional monitoring methods that require intrusive hardware installation, NILM leverages advanced computational techniques to analyze electrical signals and infer appliance usage patterns, thus reducing cost and complexity. This approach has gained significant traction with the integration of deep learning models, which have demonstrated superior accuracy in energy disaggregation tasks [4]-[5].

The research landscape in NILM has seen a transformative shift from conventional algorithms like Hidden Markov Models (HMMs) to more sophisticated deep learning architectures. Recent studies, such as those employing CNNs and long short-term memory (LSTM) networks, have improved the granularity and precision of load disaggregation by enabling effective feature extraction and sequence modelling. For instance, Kaselimi et al. proposed a CNN-LSTM hybrid architecture to enhance the disaggregation of energy consumption for diverse appliances, achieving improved accuracy metrics in multiple household scenarios [8]. Similarly, Massidda et al. introduced a fully CNN integrating semantic segmentation and multilabel classification techniques to enhance the recognition of appliance activation states, outperforming existing benchmarks [9].

Parallel advancements have also explored novel methods for temporal and frequency-based disaggregation. Li et al. proposed a double-branch bi-directional temporal convolution network (DBB-TCN) to model both long-term and short-term appliance characteristics effectively, addressing challenges such as varying operating conditions and user interference [7]. Furthermore, Aman et al. explored transfer learning approaches, leveraging pretrained models like ResNet-18 and DenseNet121 for appliance identification, showcasing the utility of integrating domain adaptation techniques for NILM applications [10].

Deep learning architectures, such as LSTM networks, gated recurrent units (GRUs), and CNNs, have become foundational in NILM research. For instance, Suryalok Dash and N.C. Sahoo proposed a deep sequence-to-point learning neural architecture specifically designed for energy disaggregation using aggregate consumption data. This approach demonstrated a substantial reduction in prediction errors compared to traditional methods, achieving at least a 56% improvement for major appliances. The study underscores the potential of advanced neural networks in addressing the challenges of NILM, such as variability in consumption patterns and noise in aggregate measurements [11]. Similarly, Kaselimi et al. introduced a multi-channel recurrent CNN that incorporates reactive, apparent, and active power data to enhance robustness against noise and improve disaggregation accuracy. By utilizing recurrent properties and multiple data channels, their method achieved superior results over existing approaches, demonstrating the importance of incorporating diverse input variables in NILM models [12]. Moreover, hybrid architectures, such as the one-dimensional convolutional and recurrent neural network (1D CNN-RNN) model proposed by Cavdar and Faryad, have also shown promise in combining feature extraction capabilities with temporal modelling, thus providing high accuracy in energy disaggregation even on low-cost embedded platforms [13].

In recent years, novel models such as WaveNet have further advanced NILM by offering higher computational efficiency and lower error rates. These models effectively capture complex temporal patterns in energy data, making them particularly effective for both disaggregation and on/off detection of appliances [14]. The integration of such state-of-the-art techniques into NILM systems aligns with the broader goals of energy efficiency, sustainability, and user awareness in smart grid ecosystems. The literature highlights the continuous evolution of energy disaggregation technologies, emphasizing their transformative potential in shaping energy-efficient smart buildings.

The NILM involves estimating the power consumption of individual appliances from the aggregated power demand measured by a single electric meter monitoring multiple-devices [15]. Over recent years, advancements in machine learning and optimization techniques have significantly contributed to NILM research [16] [17]. Early studies explored approaches utilizing k-Nearest Neighbours (k-NN), Support Vector Machines (SVM), and Matrix Factorization [18], [19].

Effective NILM approaches must process real power measurements sampled at intervals of seconds or minutes. Among these, the HMM has emerged as a widely used technique due to its capability to model transitions in energy consumption levels for specific appliances [20]. Subsequent studies have focused on enhancing the expressive capacity of HMM-based methodologies [2], [22]. Recently, NILM has been reframed as a multi-label classification problem, where the objective is to identify active appliances at each time step by associating the aggregate power value with a binary label vector representing appliance activity. This reformulation has been addressed through various methods [23]– [25], although deriving precise power consumption for individual appliances remains a challenge.

Deep learning-based approaches have gained considerable attention for NILM due to their promising disaggregation performance. Kelly and Knottenbelt have pioneered the application of Deep Neural Networks (DNNs) to NILM and introduced the concept of "Neural NILM" [26]. This approach models NILM as a nonlinear regression problem, training separate neural networks for each appliance to predict their load profiles from corresponding segments of aggregated data. The authors proposed three neural architectures: a LSTM-based RNN, a Denoising Autoencoder (DAE), and a regression model for predicting appliance start time, end time, and average power demand.

The LSTM architecture leverages its ability to capture long-term dependencies in time-series data, combining stacked LSTM layers with a CNN for feature extraction. NILM was also addressed as a noise reduction problem in which the disaggregated load represents the clean signal, and the aggregated signal includes noise from other appliances and measurement errors. For this purpose, the DAE architecture, consisting of convolutional and fully connected layers, achieved superior performance compared to the LSTM-based model and traditional methods like HMMs and Combinatorial Optimization [27].

Further empirical studies have explored deep learning techniques for NILM, including regression models for estimating transient power demand and RNNs with LSTM units for temporal modeling [28]. Zhang et al. [29] proposed sequence-to-point learning, treating the midpoint of an appliance load window as the output of a neural network given an input aggregate power window. Bonfigli et al. [30] enhanced the DAE architecture by incorporating pooling, up sampling layers, and a median filter during post-processing to reconstruct the disaggregated signal.

Shin et al. [31] introduced the Subtask Gated Network (SGN), which integrates two CNNs: a regression subnetwork for initial power estimation and a classification subnetwork for binary appliance state detection. Their approach, combining regression and classification outputs, demonstrated improved performance over earlier methods [22, 24]. Building on this, Chen et al. [32] augmented the SGN framework with a Generative Adversarial Network (GAN), where a generator produced load patterns for appliances, improving prediction accuracy through adversarial training.

While RNNs remain prevalent in sequence modeling, CNNs have consistently outperformed RNNs in NILM tasks [33]-[35]. For instance, a CNN-based DNN combined with data augmentation and advanced post-processing improved the detection of appliance activation with limited data [23]. Attention mechanisms have also been introduced, demonstrating notable improvements in disaggregation when applied within the same household, although generalization to unseen households remains limited [34]. The use of architectures, such as those based on machine translation models with encoder-decoder RNN layers, has shown promise but involves time-intensive training and testing [35], [39]-[41].

The organization of the manuscript is as follows. Methodology is discussed in section 2, results and discussions are presented in section 3, and finally conclusion and future scope of the work is discussed in section 4.

2 Methodology

2.1 Problem Formulation

The NILM refers to the process of determining the power consumption of individual appliances from the aggregate power usage recorded by a single meter. Consider a scenario where multiple appliances operate under a shared electric meter, each appliance having only two states: ON and OFF. When an appliance is in the ON state, it is assumed to consume a constant amount of power [36]. In such a case, the aggregate power measured by the meter at a given time can be represented in equation 1.

$$P(t) = \sum_{k=1}^{N} P_i(t).S_i(t) + \epsilon_t \qquad (1)$$

In (1), N denotes the total number of appliances in the household, $P_i(t)$ represents the power consumption of the i^{th} appliance at time t, and $S_i(t)$ indicates its operational state at the same time. The variable ϵ_t accounts for measurement noise at time t.

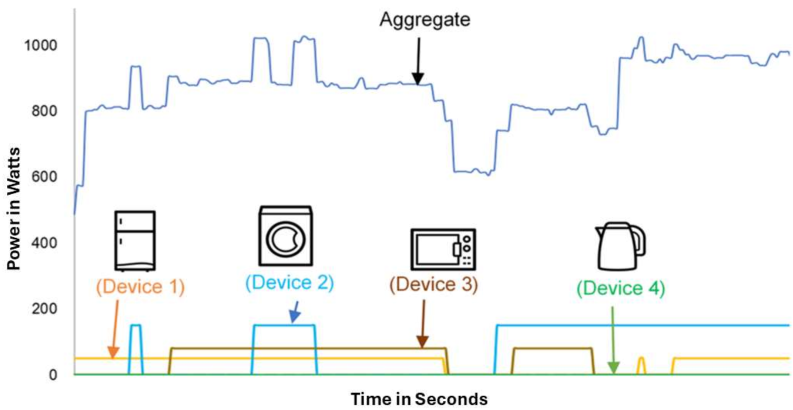

Figure 1: Illustration of the aggregate load profile and the NILM.

Let E represent the cumulative energy consumption recorded by the smart meter over this period. Here, $P_i(t)$ is a value within a defined power range for the appliance, and $S_i(t)$ is a binary variable that assumes a value of 1 when the appliance is active (ON) and 0 otherwise. By avoiding the need for sensors at each individual appliance, NILM facilitates the estimation of individual power consumption $P_i(t)$ based solely on the aggregated data $P(t)$ recorded by the meter.

2.2 Parallel Appliance Classification and Load Prediction

This section presents the detailed architecture of the DNN designed to address the NILM problem, utilizing TCN. The proposed framework is divided into two components: a classification network and a regression network. Both components are structured with distinct encoder-decoder architectures.

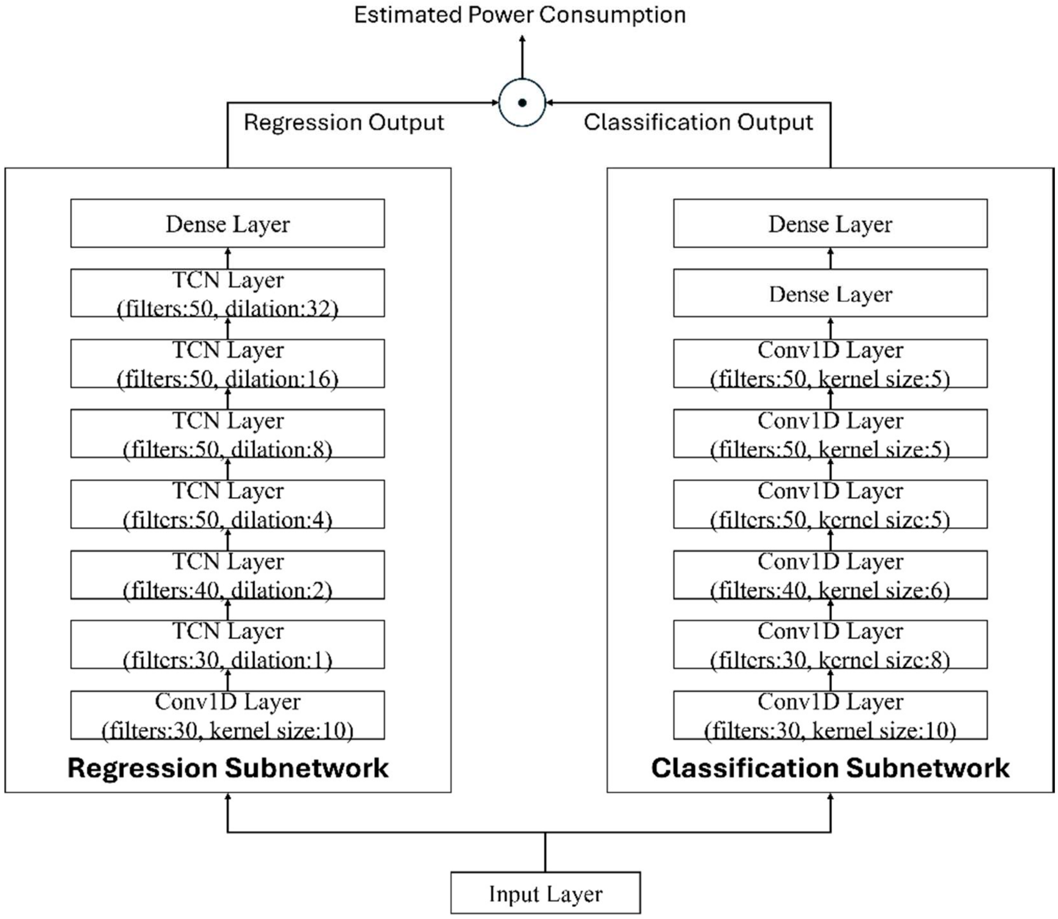

Figure 2: Proposed architecture using TCN layer.

Let $f_{reg}: R_+^L \rightarrow R_+^L$ represent the appliance power estimation model. The regression subnetwork is designed to learn the mapping $p_t^L = f_{reg}(x_t^L)$. The architecture of the regression subnetwork is structured as follows.

A) Encoder:

The encoder network consists of a CNN with four one-dimensional convolutional layers (Conv1D) utilizing the ReLU activation function. These layers process the aggregated input signal to extract the appliance-specific signature in the form of a set of feature maps. Subsequently, a Temporal Convolutional Network (TCN) layer is employed to take the extracted feature maps as input and generate a sequence of hidden states that encapsulate the temporal and contextual information from the aggregated signal. The TCN is specifically designed to handle sequence modeling tasks effectively by leveraging causal convolution and dilation to capture long-range dependencies. Unlike recurrent architectures, such as RNNs or LSTMs, the TCN computes the entire sequence in parallel, ensuring higher computational efficiency. Additionally, residual connections are incorporated within the TCN to mitigate the vanishing gradient problem and enhance gradient flow during training.

B) Decoder:

The decoder network is designed to map the high-level features extracted by the encoder back to the target output sequence. It comprises two fully connected layers (Dense layers), each tailored to progressively refine the feature representation. The first Dense layer serves as an intermediate transformation layer, where the number of units is chosen based on the dimensionality of the encoder's output and the complexity of the mapping required. This layer applies a non-linear activation function, such as ReLU, to enhance the model's capacity to capture complex patterns and relationships in the feature space. The second Dense layer is configured with a number of units equal to the sequence length L, ensuring that the output matches the temporal resolution of the target sequence. This layer often uses a linear activation function, as it directly predicts the final output values without additional non-linear transformations. By structuring the decoder in this way, it effectively reconstructs the target sequence while preserving the temporal characteristics of the input data.

Let $f_{cls}: R_{+}^{L} \rightarrow [0,1]^{L}$ denote the appliance state estimation model, where R_{+}^{L} represents the non-negative input feature space and $[0,1]^{L}$ signifies the probability space for appliance states. The classification subnetwork is tasked with learning the mapping $s_t^L = f_{cls}(x_t^L)$, where s_t^L represents the predicted appliance state at time t for each of the L appliances, and x_t^L is the corresponding input signal.

The classification subnetwork adopts a sequence-to-sequence architecture, which comprises six convolutional layers followed by two fully connected layers. The convolutional layers serve to extract hierarchical features from the input signal by applying filters that capture both local and temporal dependencies, effectively identifying patterns related to appliance states. Each convolutional layer is equipped with an activation function (e.g., ReLU) to introduce non-linearity and enhance the model's expressive power. Following the convolutional layers, two fully connected layers are employed to refine the feature representations and map them to the probability space $[0,1]^{L}$. This configuration ensures that the model can produce robust and discriminative state predictions for each appliance.

2.3 Temporal Convolutional Network

A residual block in a TCN is a fundamental architectural element designed to enhance model performance while addressing the challenges of vanishing gradients and information degradation in deep networks. The block typically consists of a series of dilated causal convolutions, followed by weight normalization, non-linear activation functions (e.g., ReLU), and dropout for regularization. The key feature is the residual connection, which bypasses the convolutions and directly adds the input to the output of the convoluted layers. This ensures that essential information from earlier layers is preserved and allows gradients to flow more effectively during backpropagation.

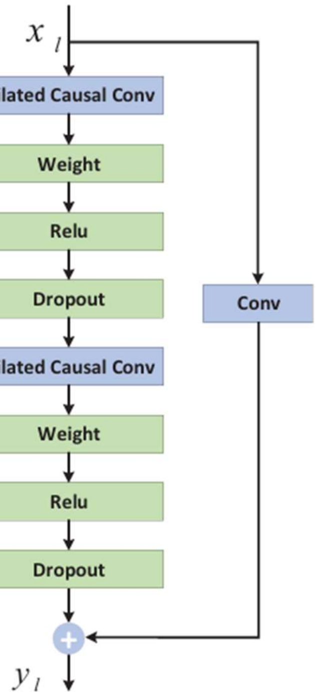

Figure 3: Residual block in TCN.

The residual structure enables the TCN to learn deeper temporal dependencies in sequential data without losing stability. By using dilation, it significantly extends the receptive field while keeping the computational cost manageable. This makes TCNs particularly suitable for tasks requiring long-range temporal context, such as time-series forecasting, sequence modelling, and audio signal processing.

3 Results and Discussion

In this section, we present the experiments conducted to evaluate our TCN-based classification approach. First, we outline the datasets, performance metrics, and the experimental procedure employed. Then, we present and analyze the results obtained.

3.1 Datasets

To assess the performance of our algorithm and ensure a fair comparison with state-of-the-art methods, we utilize two publicly available real-world datasets and adopt the same training and testing partitions as outlined in prior studies [29], [31], [32]. The first dataset, the Reference Energy Disaggregation Data Set (REDD) [37]-[39], contains data from six households in the USA, with aggregate power consumption recorded at a 1-second sampling interval and appliance-level power consumption recorded at 3-second intervals. In alignment with previous studies, we focus on the three appliances with the highest energy consumption: dishwasher (DW), fridge (FR), washer dryer (WD) and microwave (MW). The training set is constructed using data from houses 2–6, while house 1 is reserved for testing. The pre-processed version of the REDD dataset is sourced from the authors of [31].

The second dataset, the Domestic Appliance-Level Electricity (UK-DALE) dataset [33], encompasses over two years of energy consumption data from five households in the UK, sampled at 6-second intervals. For this dataset, experiments are conducted on the five appliances with the highest energy consumption: dishwasher (DW), fridge (FR), kettle (KE), microwave (MW), and washer dryer (WD). Following the approach in previous works [29], [31], [32], houses 1, 3, 4, and 5 are used for training, while house 2 is designated for testing. The pre-processed UK-DALE dataset is obtained from the authors of [27].

It is important to highlight that both datasets are evaluated under an unseen setting, where training and testing are performed on different households. This approach effectively tests the generalization capabilities of the model, a critical attribute for Non-Intrusive Load Monitoring (NILM) algorithms. In real-world applications, NILM systems are often deployed in environments that differ from those used during training, making the ability to generalize to unseen scenarios highly desirable.

3.2 Network Design

In the Neural NILM approach, a separate network is trained for each target appliance using mini batches of 32 examples. Input sequences undergo mean and variance standardization, while target data are normalized using min-max scaling based on the appliance's power consumption range in the training set. Training utilizes a sliding window technique with overlapping windows of length L and a hop size of one sample, ensuring the window size is adequate to capture the full activation of an appliance without excessive interference from others.

Each network is trained with Stochastic Gradient Descent (SGD) with Nesterov momentum (0.9), using a loss function $L = L_{out} + L_{cls}$, where L_{out} is the Mean Squared Error (MSE) for regression, and L_{cls} is the Binary Cross-Entropy (BCE) for classification. Training spans up to 100 epochs with an initial learning rate of 0.001, reduced progressively by a decay factor of 10^{-6}. Early stopping prevents overfitting by halting training when validation error increases. Hyperparameters such as the number of filters (F), kernel size (K) are optimized using grid search on a validation set. The disaggregation phase, also employing a sliding window, reconstructs the signal using a median filter for overlapping segments, as proposed in [25]. The implementation is carried out in Python using TensorFlow and experiments are run on NVIDIA A5000 GPUs.

3.3 Real-time scheduling

Table 1, highlighting metrics such as Mean Absolute Error (MAE), Signal Aggregation Error (SAE), and F1-score for different appliances, namely microwave (MW), fridge (FR), dishwasher (DW), and washing machine (WD), as well as the overall performance across all appliances. The comparison spans several models, including FHMM, DAE, Seq2Point, ResNet, and two Temporal Convolutional Network (TCN) variants, including the proposed TCN-based classification framework.

The results indicate a significant performance gap between traditional methods and advanced deep learning models. FHMM, the baseline method, demonstrates the highest MAE and SAE values, coupled with notably low F1-scores, underscoring its limited capability to accurately classify appliances or predict their energy consumption. In contrast, DAE and Seq2Point models achieve improved performance, with Seq2Point showing slightly better F1-scores across appliances, suggesting enhanced classification accuracy. However, their MAE and SAE remain relatively higher compared to ResNet and TCN-based models.

The proposed TCN-based classification framework outperforms all other models across all metrics. It achieves the lowest MAE (12.05 overall) and SAE (7.29 overall), signifying superior load prediction fidelity. Moreover, its F1-score (87.08 overall) highlights its exceptional classification accuracy, particularly for appliances like the fridge and washing machine, where it achieves F1-scores of 94.51% and 93.23%, respectively. These results are attributable to the TCN's ability to capture long-term temporal dependencies and handle overlapping energy signatures effectively. This performance underscores the proposed model's robustness and suitability for real-world NILM applications, offering a scalable and efficient solution for disaggregating household energy data.

Table 1: Disaggregation performance for REDD Dataset (The best performance was highlighted with bold font).

Model	Metric	MW	FR	DW	WD	Overall
FHMM [34]	MAE	89.56	99.76	103.12	98.43	97.71
	SAE	66.03	47.65	94.33	97.23	76.31
	F1 (%)	11.57	33.23	12.65	11.33	17.19
DAE [25]	MAE	23.23	29.01	26.67	25.77	26.17
	SAE	19.88	20.67	21.45	23.34	21.33
	F1 (%)	58.67	75.87	47.98	45.23	56.93
Seq2Point [24]	MAE	26.98	27.13	24.65	25.44	26.05
	SAE	17.77	18.55	22.76	16.54	18.90
	F1 (%)	66.65	75.88	48.13	45.64	59.07
ResNet [35]	MAE	11.76	23.77	12.65	18.45	16.65
	SAE	17.67	14.65	15.78	11.12	14.80
	F1 (%)	69.18	83.12	57.87	69.23	69.85
TCN [36]	MAE	10.23	19.67	11.67	13.55	13.78
	SAE	8.76	7.23	10.45	8.77	8.80
	F1 (%)	79.87	76.23	67.23	81.17	76.12
Proposed TCN Classification	MAE	**8.76**	**17.43**	**10.78**	**11.23**	**12.05**
	SAE	**6.76**	**5.89**	**9.22**	**7.32**	**7.29**
	F1 (%)	**83.17**	**94.51**	**77.43**	**93.23**	**87.08**

The results presented in Table 2 indicate a significant performance gap between traditional methods and advanced deep learning models. FHMM, the baseline method, demonstrates the highest MAE and SAE values, coupled with notably low F1-scores, underscoring its limited capability to accurately classify appliances or predict their energy consumption. In contrast, DAE and Seq2Point models achieve improved performance, with Seq2Point showing slightly better F1-scores across appliances, suggesting enhanced classification accuracy. However, their MAE and SAE remain relatively higher compared to ResNet and TCN-based models. The conventional TCN architecture as presented in [36] doesn't have classification and regression sub-networks. In the proposed model, classification and regression sub-networks have been implemented for leading the better performance in disaggregating induvial appliance from the aggregated load profile.

The proposed TCN-based classification framework outperforms all other models across all metrics. It achieves the lowest MAE (12.05 overall) and SAE (7.29 overall), signifying superior load prediction fidelity.

Moreover, its F1-score (87.08 overall) highlights its exceptional classification accuracy, particularly for appliances like the fridge and washing machine, where it achieves F1-scores of 94.51% and 93.23%, respectively. These results are attributable to the TCN's ability to capture long-term temporal dependencies and handle overlapping energy signatures effectively. This performance underscores the proposed model's robustness and suitability for real-world NILM applications, offering a scalable and efficient solution for disaggregating household energy data.

Table 2: Disaggregation performance for UKDALE Dataset (The best performance was highlighted with bold font).

Model	Metric	MW	FR	KE	DW	WD	Overall
FHMM [34]	MAE	43.52	60.88	38.12	48.33	67.41	51.65
	SAE	40.32	50.89	35.33	46.05	64.32	47.38
	F1 (%)	4.22	33.23	9.15	11.39	4.20	12.43
DAE [25]	MAE	13.24	17.32	10.62	22.25	13.87	15.46
	SAE	10.45	8.34	5.23	18.18	10.23	10.48
	F1 (%)	24.34	80.44	94.78	54.77	24.65	55.79
Seq2Point [24]	MAE	12.34	17.56	10.91	15.69	10.37	13.37
	SAE	10.55	8.22	5.20	10.25	8.44	8.53
	F1 (%)	45.22	80.45	94.66	50.32	49.01	63.92
ResNet [35]	MAE	8.44	15.61	6.34	8.51	8.38	9.46
	SAE	5.37	6.74	4.99	4.68	5.44	5.44
	F1 (%)	63.88	85.22	98.34	63.80	63.06	74.86
TCN [36]	MAE	7.33	13.56	5.46	6.44	7.98	8.154
	SAE	4.77	6.09	3.55	3.82	4.66	4.57
	F1 (%)	71.65	87.33	97.62	68.93	72.33	79.57
Proposed TCN Classification	MAE	**6.34**	**12.45**	**4.78**	**5.34**	**6.09**	**7**
	SAE	**3.45**	**5.88**	**3.44**	**3.32**	**3.67**	**3.95**
	F1 (%)	**82.34**	**94.23**	**98.74**	**75.48**	**84.34**	**87.02**

4 Conclusion

This study validates the superiority of TCN in advancing NILM applications through a detailed evaluation on REDD and UK-DALE datasets. By effectively addressing long-term temporal dependencies and overlapping energy signatures, the proposed TCN framework achieves notable improvements in load prediction accuracy and appliance classification. Compared to existing models such as FHMM, DAE, Seq2Point, and ResNet, the proposed TCN-based classification system demonstrates the lowest MAE and SAE while achieving the highest F1-scores, particularly excelling in disaggregating challenging appliances like fridges and washing machines.

Few applications of the proposed work include real-time feedback for users to adjust their energy consumption patterns for facilitating dynamic pricing models and demand-side management strategies [42]-[43], detects anomalies in appliance energy consumption, indicating potential faults or inefficiencies, and be integrated with IoT-based home automation systems for intelligent control of devices [44].

The integration of multi-task learning in the TCN architecture further enhances the scope of the work for computational efficiency and system adaptability, ensuring robust performance even under noisy conditions. The lightweight and scalable design, coupled with superior accuracy metrics, underscores the framework's suitability for real-world deployment in smart grid systems and residential energy monitoring. These findings emphasize the transformative potential of TCN-based NILM systems in promoting energy efficiency and advancing the capabilities of modern energy management solutions. By combining TCNs with attention mechanisms or transformers to further enhance classification accuracy and load prediction fidelity. Furthermore, by exploring hybrid models integrating TCNs with graph neural networks (GNNs) for spatial-temporal energy analysis.

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