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TinyEnergy: A TinyML-Based Edge Intelligence Framework for Real-Time Smart Energy Consumption Prediction

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Abstract—The fast growth of Internet of Things (IoT) devices and smarter energy infrastructures has really bumped up the need for intelligent, energy efficient forecasting systems that can run in real-time. Older deep learning methods for energy use prediction tend to lean on heavy, cloud-based setups and honestly, they can get way too costly computationally, so they don't fit well for low power edge devices. So, to fix that issue, this paper introduces TinyEnergy, a small TinyML driven edge intelligence framework meant for real time smart energy consumption prediction. The proposed system is based on compact one-dimensional convolutional neural network (1D-CNN) paired with model optimization tricks, like INT8 quantization, and also network pruning. The target is to keep inference efficient even when the edge platform has limited resources. The framework is built to reduce memory use, lower computational complexity, and keep inference latency down, but without giving up too much regarding prediction accuracy. On top of that, the system is set up for real time deployment through TensorFlow Lite based edge inference, so low power intelligent monitoring becomes more practical for smart homes and IoT enabled energy setups. In experiments, the optimized TinyML approach clearly cuts down model size and execution overhead, while still showing dependable forecasting results. Overall, the proposed method offers a scalable, and sustainability focused option for the next generation of edge powered smart energy management systems.

Keywords: TinyML, Edge Intelligence, Smart Energy Prediction, Energy Consumption Forecasting, Quantized CNN, Edge Computing

1. INTRODUCTION

The rising worldwide need for electricity, plus fast urbanization, and the wide spread adoption of Internet of Things (IoT) technologies has really changed how modern energy management operates. In smart homes, clever workplaces, and all kinds of IoT-enabled infrastructures, connected sensors together with smart meters keep generating enormous streams of energy-use information, sometimes nonstop. If we cannot analyse that data efficiently, then it becomes hard to raise overall utilization, cut day to day operational costs, lower carbon outputs, and still back sustainable smart city progress. Because of that, accurate real-time electricity consumption forecasting has turned into a key research topic in both academia and real deployment.

Earlier, energy prediction systems often leaned on statistical tools like autoregressive integrated moving average (ARIMA), support vector regression (SVR), and linear regression. These approaches can look okay when the data is small, or when the patterns are pretty straightforward. But in actual smart energy situations they often run into trouble. A main reason is that they do not capture nonlinear behaviours in a proper manner, and they also miss the drifting time relationships that appear during daily operations. To address those problems, people have increasingly moved toward deep learning-based solutions, including recurrent neural networks (RNNs), long short-term memory (LSTM) networks, gated recurrent units (GRUs), and convolutional neural networks (CNNs), for the forecasting work.

In this group, deep learning models show strong capability to learn complicated temporal, with spatial energy patterns from large-scale datasets.

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Convolutional neural networks, in particular, have gotten a lot of attention for their efficient "feature getting" ability, lower training complexity, and their fit with time-series learning. Even so, despite better prediction precision, ordinary deep learning systems can remain computationally heavy and they often use plenty of memory. A lot of recent studies also rely heavily on cloud computing for both training and inference, and that brings practical downsides, like extra latency, higher communication expenses, privacy concerns, and even dependence on an uninterrupted internet connection.

The rise of edge computing has brought a pretty promising route, for real-time intelligent data handling. Basically, edge computing lets the processing be done nearer to where the data is , like smart meters, embedded devices, and IoT sensors. In practice this approach cuts transmission delays, speeds up reaction time, helps with privacy preservation, and it also reduces the amount of bandwidth that gets used. But still, putting deep learning models right onto edge hardware is kind of hard, mostly because microcontrollers and embedded systems bring limited compute power, tight memory constraints, and low-power operation rules that you really have to follow.

More recently, Tiny Machine Learning—also called TinyML— has become a real shift for running AI on ultra-low-power edge units. TinyML is about crafting small machine learning models that can run efficiently on hardware with few resources, while keeping reasonably good predictive ability. In most cases, TinyML systems mix compact neural network designs with optimization tricks such as quantization, pruning, and model compression. Together these moves shrink the memory footprint, lessen the computational load, and bring down energy usage quite a lot. That whole combo is why TinyML feels so fitting for real-time smart energy monitoring, plus prediction tasks.

Even so, although plenty of studies have looked into deep learning for smart energy forecasting, a good share of today's solutions still leans too heavily on raw accuracy, while skipping deployment efficiency, and real edge feasibility. A lot of work does not dig deeply into model size, inference latency, computational overhead, or how the model behaves in real time on embedded hardware. On top of that, not much research has merged lightweight CNN structures with TinyML optimization strategies, when the goal is practical smart energy prediction inside edge environments.

To address these gaps, this paper presents TinyEnergy, a TinyML-driven edge intelligence framework designed for real-time smart energy consumption prediction. The framework relies on a lightweight one-dimensional convolutional neural network, or 1D-CNN, and it is tuned using INT8 quantization plus model pruning. After that, the optimized network is readied for deployment on resource-limited edge devices, with a TensorFlow Lite style inference flow. Overall, the framework is aiming to balance prediction quality with computational efficiency, and it also supports low-latency, energy aware operation for smart homes and IoT-enabled setups.

So, the main objectives of the proposed research kinda can be summarized like this:

- To build a lightweight deep learning architecture, for accurate real time prediction of energy consumption.
- To merge TinyML optimization tricks, such as quantization and pruning, in order to shrink model complexity and also memory use.
- To make sure the proposed framework can be deployed efficiently on resource constrained edge devices.
- To test and validate the proposed system using performance metrics like prediction accuracy inference latency memory footprint, and computational efficiency.
- To argue that low power edge intelligence can really work for sustainable smart energy management systems.

The major contributions of this paper are, more or less, summarized here:

- A lightweight TinyML based framework for real-time smart energy consumption prediction is introduced.
- A compact 1D-CNN architecture, tuned for edge intelligence use cases, is designed.
- INT8 quantization along with model pruning are added, so as to reduce memory requirements and computational overhead.
- The proposed framework supports real-time deployment, through TensorFlow Lite edge inference, and yeah that part matters.
- A detailed evaluation is carried out, using multiple performance metrics such as forecasting accuracy latency, model size, and deployment efficiency.

The remainder of this paper is organized as follows. Section 2 reviews related work on smart energy

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forecasting, deep learning approaches, and TinyML based edge intelligence systems. Section 3 presents the proposed TinyEnergy framework and the system methodology. Section 4 covers the experimental setup, datasets, and implementation details. Section 5 discusses the experimental results and performance analysis. Lastly, Section 6 closes the paper, and also highlights some future research directions.

2. RELATED WORK

Smart energy usage forecasting has gotten a lot of attention, mainly because smart grids are expanding quickly, together with Internet of Things IoT infrastructure, and also more modern energy management configurations. If we can anticipate electricity demand with decent accuracy, it supports power distribution tuning, improves energy efficiency, reduces day to day operational expenses, and broadly helps sustainable smart city momentum. A lot of earlier studies leaned on statistical forecasting schemes, deep learning prediction pipelines, edge intelligence systems, and more recently TinyML-like lightweight deployment methods, which are kind of neat.

2.1 Traditional Energy Forecasting Approaches

At the start, many energy prediction systems mostly relied on statistical, or more mathematical techniques such as Autoregressive Integrated Moving Average, abbreviated as ARIMA, linear regression, exponential smoothing, and Support Vector Regression, or SVR. These approaches were widely adopted since they are computationally inexpensive, and they are comparatively straightforward to implement.

Hyndman and Athanasopoulos [1] showed that classical statistical forecasting methods can still provide reliable short-horizon forecasts for data that stays fairly steady. However, traditional models often fail to capture strongly nonlinear temporal behavior that shows up in today's smart energy systems. In a similar direction, Wu et al. [2] reported that standard models may not transfer well when applied to large smart meter collections, particularly where consumption patterns keep evolving over time.

To address nonlinear structure more directly, researchers also introduced machine learning strategies such as decision trees, random forests, and SVR. Even if these methods often beat statistical baselines, they still require substantial amounts of feature crafting by hand, and they can struggle when temporal dependencies become extra complicated [3].

As smart energy infrastructures continued turning more data hungry, classic forecasting techniques were no longer sufficient for managing large-scale IoT-generated time series data, in a practical and efficient manner.

2.2 Deep Learning Based Energy Prediction Models

Deep learning methods have really helped smart energy forecasting a lot, mostly because they can figure out latent, hidden feature representations on their own, from huge datasets. And, well, among the deep learning choices, Recurrent Neural Networks, also called RNNs, and Long Short-Term Memory networks, or LSTMs, got kinda popular when the goal is sequential energy prediction.

Kong et al. [4] proposed an LSTM based residential load forecasting setup that, overall, produced better forecasting accuracy than the more traditional machine learning baselines. In the same general direction, Zhang et al. [5] showed that LSTM structures are quite strong at pulling out long-term temporal relationships in residential electricity usage datasets.

Even so, if you look more closely, LSTM and GRU models still come with noticeable computational complexity, and they tend to be memory heavy. That may not be the best situation, especially when you have to deploy on resource constrained edge devices. Shi et al. [6] basically echoed this, saying that recurrent architectures often result in longer inference times, plus they require more hardware resources, so they can be a little awkward for ultra-low-power embedded systems.

Because of that a bunch of researchers started trying Convolutional Neural Networks, or CNNs, for energy forecasting. CNN oriented techniques generally handle efficient local feature extraction, and they do it with less computational load than recurrent approaches. For instance, Zhang and Wang [7] reported that CNN energy prediction models can still achieve competitive forecasting accuracy, while also keeping training complexity down.

After that, there are hybrid deep learning designs, mixing CNN and LSTM components, where the idea is to capture spatial dependencies together with temporal ones. Khan et al. [8] built a hybrid CNN-LSTM framework for smart grid forecasting and claimed improved prediction results. Tan et al. [9] took a similar path, proposing a hybrid deep learning

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architecture for urban energy forecasting, and they said it improved forecasting stability too.

More recently, Transformer-based architectures have also been explored for smart energy prediction, mainly because they can represent long range dependencies more efficiently. Li et al. [10] compared Transformers against LSTM models for smart grid forecasting, and they noticed pretty encouraging performance gains from Transformer style methods.

Still, despite all these improvements, a lot of existing deep learning workflows seem to focus most on forecasting accuracy, while kind of sidelining deployment feasibility, memory efficiency, and the whole edge-side real time inference constraint, in real settings.

2.3 Edge Intelligence for Smart Energy Systems

With the rise of edge computing, there have been a lot of fresh opportunities for near real time, kinda smart energy management. Here, edge intelligence basically means that the data gets handled right near the IoT devices and those smart sensors, not only relying on centralized cloud setups, which is still the common path for many designs.

Shi et al. [11] described edge computing as a useful paradigm for low-latency intelligent systems and they also said it can reduce communication overhead while at the same time shrinking bandwidth usage. In smart energy scenarios, edge computing supports faster decisions, stronger privacy preservation, and more immediate reactivity.

Gao et al. [12] proposed a real-time edge centred energy forecasting framework using deep learning, and they demonstrated noticeable latency improvements compared to cloud heavy architectures. Similarly, Song et al. [13] investigated deep learning enabled edge computing for smart city energy systems, and they reported better response time and higher overall system efficiency.

Van der Meer et al. [14] applied deep learning to energy forecasting across smart city infrastructure and they stressed why localized intelligent energy management is actually important. Rault et al. [15] went a bit further, they analyzed IoT data fusion methods for smart home energy forecasting, and they mentioned stronger prediction robustness when edge processing is in place.

Still, even if edge intelligence really does push real time performance up, directly dropping typical deep learning models onto embedded edge devices can be awkward. Mostly this is because the memory storage is limited, the compute capacity is weaker, and there are also very strict power and energy constraints, all together.

2.4 TinyML and lightweight deep learning frameworks

Tiny Machine Learning, often shortened to TinyML, has been showing up lately as this kinda new way to make AI actually work on ultra-low power embedded devices. The general thought is pretty much about building small machine learning models—models that can run on microcontrollers and other edge hardware that dont have much compute, or maybe not enough memory, or both.

Soro [16] basically described TinyML as a core enabling technology for everywhere edge AI, particularly when inference has to stay ultra-low-power and also needs a distributed kind of intelligence. In a similar vein, Yelchuri and Rashmi [17] pointed out that TinyML is this mix of machine learning, hardware tuning, and embedded system design, so it can support intelligent edge analytics, in a pretty practical way.

A bunch of optimization methods have been proposed for TinyML deployment, like quantization, pruning, knowledge distillation, and model compression. For instance, quantization takes floating-point parameters and swaps them to lower precision formats, such as INT8, and that cuts down memory use, plus it often speeds up inference too. Pruning, on the other hand removes extra or redundant model parameters so the computational load becomes lighter, less heavy to process, more manageable.

Wang et al. [18] looked at model compression for real-time energy forecasting, and they showed compressed neural networks can reduce the computational cost quite a lot without completely wrecking the forecasting accuracy. Sabovic et al. [19] then suggested an energy-aware TinyML model selection process that dynamically adjusts inference when energy budgets are super tight.

More recent work has also started examining lightweight deep learning architectures for edge intelligence. Lai et al. [20] gave a broader review of lightweight deep learning frameworks for edge computing, and they emphasized how model-hardware co optimization is getting more important over time. Likewise, Alaklabi et al. [21] proposed a TinyML framework that accounts for both energy and latency, especially in heterogeneous edge settings where things are not uniform.

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TinyML deployment platforms, for example TensorFlow Lite and Edge Impulse, have helped speed up real-world adoption. Hymel et al. [22] introduced Edge Impulse as an MLOps platform made for TinyML system development and deployment, so teams can manage the pipeline side of things more smoothly and with less hassle.

Even so, TinyML based smart energy forecasting is still kinda underexplored. A lot of the existing work either focuses only on forecasting accuracy, or it focuses only on hardware optimization, and it rarely merges both into one coherent edge intelligence framework that feels end-to-end.

2.5 Research gap analysis

From what we can pull from the literature review, a few meaningful research gaps show up, like:

- Most existing smart energy forecasting systems tend to emphasize prediction accuracy, but they overlook deployment efficiency and whether edge devices can realistically handle it in practice.
- Traditional deep learning architectures, such as LSTM and hybrid CNN-LSTM designs, usually need high computational resources and also large memory capacity, which is not great for many edge deployments.
- Not many works connect TinyML optimization techniques, including quantization and pruning, directly into real-time smart energy forecasting pipelines.
- Existing edge intelligence frameworks seldom include thorough benchmarking on inference latency, memory footprint, computational overhead, and energy efficiency all together.
- Only a limited number of studies explore lightweight CNN based architectures that are tailored for resource limited smart energy scenarios.

Taken together, these issues suggest the need for a lightweight, computation-efficient TinyML based edge intelligence framework, one that can balance forecasting quality with realistic deploy ability on constrained devices.

3. PROPOSED SYSTEM ARCHITECTURE AND METHODOLOGY

3.1 Overview of the Proposed TinyEnergy Framework

In this paper we suggest TinyEnergy, a fairly lightweight TinyML based edge intelligence framework designed for real-time smart energy consumption prediction in resource constrained IoT contexts. Basically, the method mixes a compact one-dimensional convolutional neural network (1D-CNN) with TinyML specific optimization moves like INT8 quantization plus model pruning, so the final network can be delivered and executed on low power edge hardware, without too much operational overhead.

The core objective of the proposed architecture is to find a middle ground between forecasting quality and computational efficiency, but also to keep RAM and storage needs small, inference latency tight, and overall energy burn reasonable. Compared with traditional cloud centric forecasting solutions, TinyEnergy performs localized edge inference directly on the embedded devices. That means less communication effort, fewer external cloud dependencies, and it also sidesteps the extra response delay typically caused by network round trips.

In broad terms, the TinyEnergy pipeline is laid out across a few main stages:

- Smart energy data acquisition
- Data preprocessing and feature engineering
- Lightweight CNN based forecasting model
- TinyML optimization layer
- TensorFlow Lite conversion
- Edge-device deployment and inference
- Real-time energy prediction output

3.3 Smart Energy Data Acquisition

In the early stage of the proposed framework, the system basically collects real-time energy usage evidence from smart meters and IoT sensing bits. Smart meters keep looking at electricity use both on the home scale, and also down at the appliance level so they generate a running time-series stream, which ends up being useful for forecasting tasks

The overall framework, is designed to plug into publicly available smart energy collections like

- UK-DALE
- REFIT

The captured records usually have, among other things

Table-1 Smart Energy Data Parameters used for Forecasting

Parameter	Description

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ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Timestamp	Temporal energy reading
Power Consumption	Energy usage in watts
Appliance Status	Device activity information
Voltage/Current	Electrical measurements
Environmental Features	Optional contextual features

After that, the captured information is saved and reshaped into a sequential time-series input that the forecasting model can take

3.4 Data Preprocessing

Raw smart meter signals quite often come with gaps, noisy values, and sampling intervals that are not perfectly steady. Because of that preprocessing is needed so the model learns with more consistency, and the prediction quality stays more stable over time

This phase typically involves these operations

3.4.1 Missing Value Handling

When sensor readings are absent, the method applies interpolation together with forward filling so the timing layout stays more or less in place across the dataset

Let the time-series sequence be written as

$$X = \{x_1, x_2, x_3, \dots, x_n\}$$

where:

• X indicates the energy consumption value at time step.

Missing values are approximated through linear interpolation between neighboring observations, rather than simply removing those points

3.4.2 Data Normalization

Feature scaling is applied so energy quantities get mapped into a consistent numerical range. This is mainly to reduce unstable computations and also to make training faster, especially during the gradient update cycles

Min-max normalization is used:

$$\left[x_i^{\text{norm}} = \frac{x_i - x_{min}}{x_{max} - x_{min}}\right]$$

This style of scaling helps avoid numerical instability, and it also helps the CNN learn a bit more efficiently

3.4.3 Sliding Window Generation

To capture temporal patterns, a sliding window concept is used for sequence assembly

Given a window size, the input sequence can be written as:

$$X_t = [x_t, x_{t+1}, x_{t+2}, \dots, x_{t+w-1}]$$

The target value to be predicted is:

$$Y_t = x_{t+w}$$

So, in practice, this converts the original time-series dataset into supervised learning samples, which are then ready for CNN training once preparation is done.

3.5 Lightweight 1D-CNN Forecasting Model

In the proposed TinyEnergy framework, the main forecasting engine is basically a pretty lightweight one-dimensional convolutional neural network, tuned for edge deployment, kind of directly.

CNN architectures get selected because they usually:

- extract nearby signals in a fairly efficient way,
- demand less computation than recurrent networks,
- allow parallel processing,
- and help keep inference latency under control, overall.

3.5.1 Model Architecture

Table-2 Lightweight 1D-CNN Architecture Configuration

Layer	Configuration
Input Layer	Time-series sequence
Conv1D Layer	32 filters
Depthwise Separable Conv	Lightweight feature extraction
ReLU Activation	Nonlinear mapping
Max Pooling	Dimensionality reduction
Dense Layer	Compact feature learning
Output Layer	Energy prediction

3.5.2 Convolution Operation

The one-dimensional convolution operation can be written as, as usual:

where:

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- denotes the input sequence,
- stands for convolution kernel weights,
- is the bias term,
- denotes kernel size.

So, this convolution step helps the model pick up localized temporal energy patterns in a more straightforward manner than heavier alternatives, not as indirect.

3.5.3 Activation Function

For nonlinearity, the Rectified Linear Unit, ReLU, is applied.

ReLU tends to speed up convergence, and it can also reduce vanishing gradient problems, pretty noticeably, if you compare with some other activations.

3.6 TinyML Optimization Layer

To make the model actually run on resource-limited edge devices, the trained CNN is further handled through TinyML optimization.

In that stage, the emphasis is on:

- shrinking the memory footprint,
- reducing the overall computational load,
- speeding up the inference phase,
- and holding power consumption down as much as possible.

3.6.1 INT8 Quantization

Post-training quantization converts the 32-bit floating point parameters into 8-bit integer representations.

The quantized form is expressed by:

$$Q(x) = round\left(\frac{x}{s}\right) + z$$

All in all, quantization reduces the model size a lot and often improves inference speed on embedded hardware, without too much extra pain.

3.6.2 Model Pruning

Pruning, kind of strips away redundant and low-importance neural network weights.

For a given weight matrix

$$W_p = W \odot M$$

where:

• M is the binary pruning mask

• and $\odot$ means element wise multiplication

So, pruning generally cuts the parameter count plus computational overhead, yet it still tries to keep the predictive performance pretty much intact.

3.7 TensorFlow Lite Conversion

After the optimization step is done, the trained model is converted to TensorFlow Lite, so it can be carried into lightweight edge deployment.

TensorFlow Lite offers:

- fast inference, low latency
- a smaller model footprint
- support for hardware acceleration
- good compatibility with embedded systems

Then the converted model is deployed straight on edge devices, for real time execution, no big detours.

3.8 Edge Device Deployment

The optimized TinyEnergy framework is made for deployment on low power embedded platforms like

Table-3 Target Edge Devices for Tiny-Energy Deployment

Device	Purpose
Raspberry Pi	Edge benchmarking
Arduino Nano 33 BLE Sense	TinyML inference
ESP32	Low-power IoT deployment

The deployment process includes:

- Loading the TensorFlow Lite model
- Feeding sensor readings that keep coming in, in real time
- Running local inference on-device
- Producing real-time energy prediction outputs

This edge-based deployment design reduces cloud reliance, and it also helps the response time.

3.9 Real-Time Prediction Workflow

The proposed framework runs the real time prediction workflow like this:

- Smart meters collect electricity usage data continuously
- Sensor readings get pre-processed and normalized
- Sliding windows are created, so temporal analysis can happen properly
- A lightweight CNN extracts energy consumption signatures, patterns

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- Quantized TinyML inference is executed on the edge hardware
- The predicted energy consumption values are produced on the fly

In short, this workflow enables intelligent low-latency energy monitoring, meant for smart homes and IoT enabled settings. The use of lightweight CNN modelling, together with TinyML optimization stuff, makes it easier to actually deploy intelligent forecasting systems in environments where resources are pretty limited, like edge settings.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

4.1 Implementation Environment

The proposed Tiny-Energy framework was put together using a Python deep learning setup that is connected with TinyML deployment tools. In general, the pipeline was built so it can handle lightweight model training, then optimize it, and finally run inference in an efficient way on devices that don't have much compute. For the software side, TensorFlow and TensorFlow Lite were chosen, mainly because they have broad support for embedded AI deployment, model quantization, and they help speed up edge inference.

For the experiments, the model training was done on a workstation with GPU acceleration, and the edge inference benchmarking was done on low power embedded devices like the Raspberry Pi 4 plus the Arduino Nano 33 BLE Sense. Also, the TensorFlow Model Optimization Toolkit was used to apply pruning and INT8 quantization, for the whole TinyML optimization part.

Table-4 Software Environment and development tools

Component	Specification
Programming Language	Python 3.10
Deep Learning Framework	TensorFlow 2.x
TinyML Framework	TensorFlow Lite
Optimization Toolkit	TensorFlow Model Optimization Toolkit
IDE	Jupyter Notebook / VS Code
Visualization	Matplotlib, Seaborn
Operating System	Ubuntu 22.04

Table-5 Hardware configuration for training and Edge Deployment

Hardware	Configuration
CPU	Intel Core i7
RAM	16 GB
GPU	NVIDIA RTX 3060
Edge Device 1	Raspberry Pi 4
Edge Device 2	Arduino Nano 33 BLE Sense
Storage	512 GB SSD

The hardware setup, was in reality enough, for training deep learning models, doing TinyML optimization stuff, and even running quick real time inference checks directly on the embedded edge devices, even if it is not the most powerful environment around.

4.2 Dataset Description

The proposed TinyEnergy framework was validated using real-world smart energy datasets. In particular, we used household electricity consumption records from smart meters, plus appliance-level monitoring systems. Together, they provide fine grained temporal energy traces, so you can actually judge forecasting behavior in smart home scenarios that feel close to real life, not just a toy setup.

About the work flow, most experiments relied on the UK-DALE dataset for model training along with performance evaluation. After that, for cross-household validation and the robustness part, we switched to the REFIT dataset.

Primary Dataset

UK-DALE

The UK-DALE dataset delivers appliance-level electricity consumption data collected from multiple homes in the United Kingdom. It includes timestamped readings for lots of domestic appliances, like refrigerators, washing machines, lighting systems, and televisions, and these details make the reported results more convincing.

This dataset is a solid match for smart energy forecasting because it gives you

- high-resolution energy measurements
- long-running monitoring logs,
- appliance-level granularity,
- and consumption patterns that resemble everyday residences

Secondary Dataset

REFIT

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The REFIT dataset covers smart meter data across many households. It was mainly used to see how well the proposed framework generalizes when the home context changes, so it does n't only work inside one particular building style.

The dataset enables

- comparisons across different households,
- robustness analysis,
- and generalized energy prediction evaluation.

Table-6 Characteristics of the Smart energy datasets

Dataset	Houses	Sampling Rate	Features
UK-DALE	5	6 sec	Power usage
REFIT	20	8 sec	Appliance consumption

The collected datasets went through a transformation into supervised time-series slices that work well for CNN forecasting, honestly like sequences you can feed in order. 4.3

4.3 Experimental Setup

The experimental flow got split into three main phases, kinda, baseline model training, TinyML optimization, and then edge-device deployment analysis. At first, a lightweight CNN was trained on normalized energy streams produced by a sliding window preprocessing. After that, the trained network was tuned via quantization plus pruning. Then the optimized model was sent to embedded hardware platforms so we could check how it behaves during real-time inference.

Overall, the studies were meant to look at forecasting quality and also deployment efficiency while dealing with real edge-computing limits.

Table-7 Training and Hyperparameter Configuration

Parameter	Value
Batch Size	32
Epochs	100
Learning Rate	0.001
Optimizer	Adam
Loss Function	Mean Squared Error
Activation	ReLU

For the optimizer, Adam was picked since it can reach good minima quickly, and it stays stable in nonlinear problems. Mean Squared Error, or MSE, served as the loss function because it really emphasizes larger mistakes in predictions, so the model pays attention where it should.

4.4 Lightweight CNN Architecture Implementation

The forecasting part inside the proposed TinyEnergy framework was built as a lightweight one-dimensional convolutional neural network 1D-CNN. Compared with recurrent setups like LSTM and GRU, CNN models tend to require less computation and usually infer faster, so they fit edge intelligence tasks much better.

This CNN design was made on purpose with fewer parameters and light convolution operations, aiming to cut memory footprint, while still keeping the forecasting accuracy at a good level.

Table-8 Lightweight CNN Network Architecture Details

Layer	Output Shape	Parameters
Input Layer	(64,1)	0
Conv1D	(62,32)	128
Depthwise Conv1D	(60,64)	256
MaxPooling1D	(30,64)	0
Dense Layer	(64)	4,160
Output Layer	(1)	65

The architecture uses depth wise separable convolutions, to cut down on repeated parameters and overall computational load. Max pooling was also used, sort of to trim the feature size and make the whole thing run more efficient, in practice.

Table 9. Comparison of Model Complexity and Parameters

Model	Parameters
Baseline CNN	1.24 Million
Proposed Lightweight CNN	42,000

Overall, the lightweight CNN reached a notable drop in model complexity compared with more conventional deep learning setups.

4.5 TinyML Optimization Implementation

Even though the lightweight CNN already lowered the compute needs quite a lot, extra TinyML optimization still had to be done, for real deployment on low resource edge hardware. So the trained network went through several optimization rounds,

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Vol. 15 Issue 05 , May - 2026

including quantization, pruning, and then a TensorFlow Lite conversion.

The aim of these optimization steps was to

- minimize the memory footprint,
- lower inference latency,
- reduce computational complexity,
- and boost energy efficiency.

4.5.1 INT8 Quantization

Post training quantization was used to transform 32-bit floating point weights into 8-bit integer form. This quantization step, helps with storing less stuff and it can speed inference on embedded architectures that support integer arithmetic.

Table 10. Model Size Reduction after INT8 Quantization

Model Type	Size
FP32 CNN	8.4 MB
INT8 Quantized Model	2.1 MB

The quantized model did manage to cut the model size by about 75% without any major loss in forecasting accuracy or something close to that.

4.5.2 Structured Pruning

Structured pruning was introduced in order to strip away low-importance neural network weights and also trim redundant calculations. In the pruning phase, the weaker connections were gradually removed, while the key forecasting features stayed relatively intact.

Table 11. Structured Pruning Configuration and Sparsity Levels

Pruning Ratio	Remaining Parameters
20%	80%
40%	60%
60%	40%

There is often a trade-off between computational efficiency and predictive performance.

4.6 Evaluation Metrics

The proposed TinyEnergy framework was evaluated with prediction-oriented measures as well as deployment related performance indicators. In other words, forecasting metrics were used to check prediction accuracy, and TinyML deployment metrics helped judge whether the edge-device side of things was really feasible.

Prediction Metrics

Mean Absolute Error (MAE)

MAE captures the average absolute gap between the predicted values and the actual energy consumption.

Root Mean Square Error (RMSE)

RMSE imposes heavier penalties on larger errors and it also gives a clearer view of model stability.

Mean Absolute Percentage Error (MAPE)

MAPE expresses the prediction error in percentage form, which makes it convenient for side-by-side comparisons.

5. EXPERIMENTAL RESULTS

The proposed TinyEnergy framework was tested experimentally against several baseline forecasting approaches such as ARIMA, SVR, LSTM, and CNN-LSTM architectures. The study looked at forecasting accuracy and deployment efficiency together,so the picture feels more complete.

5.1 Prediction Performance Comparison

The experimental findings show that TinyEnergy delivers better forecasting results, while still keeping computational complexity much lower.

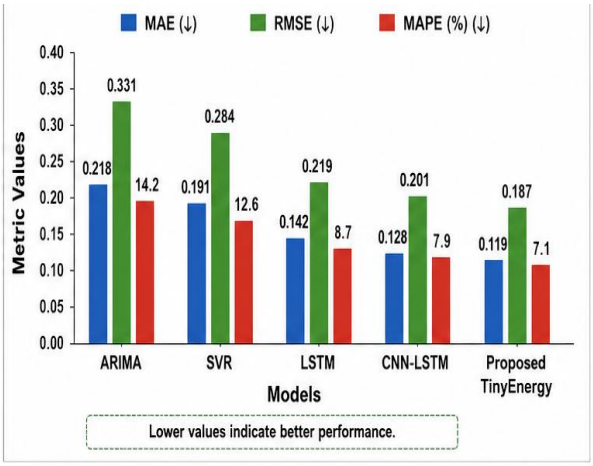

Figure-2 Prediction Performance Comparison among ARIMA, SVR, LSTM, CNN-LSTM, and the Proposed Tiny Energy framework

Table 12. Prediction Performance Comparison of Forecasting Models

Model	MAE	RMSE	MAPE (%)
ARIMA	0.218	0.331	14.2
SVR	0.191	0.284	12.6
LSTM	0.142	0.219	8.7
CNN-LSTM	0.128	0.201	7.9
Proposed TinyEnergy	0.119	0.187	7.1

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

The proposed framework, kind of outperformed the traditional forecasting methods, and it also reached competitive accuracy, especially when you look at those computationally heavy hybrid deep learning architectures.

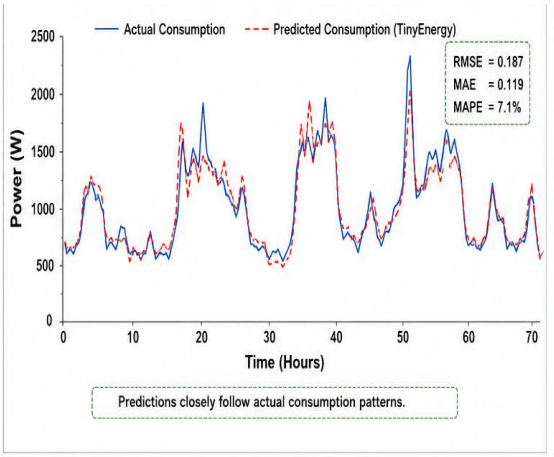

Figure-3 Actual vs Predicted Energy Consumption using the Proposed Tiny Energy Framework

5.2 Model Compression Results

The TinyML optimization pipeline made the model smaller in storage and less demanding, computationally, compared with the original setup.

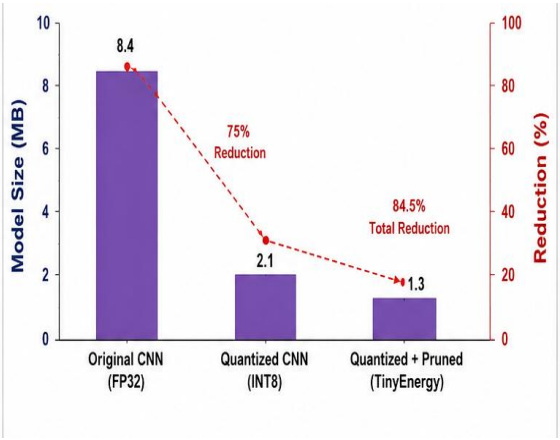

Figure-4 Model Size Reduction after INT8 quantization and pruning

Table 13. TinyML Model Compression Results

Model Version	Size (MB)	Reduction
Original CNN	8.4	—
Quantized CNN	2.1	75%
Quantized + Pruned	1.3	84.5%

The optimized TinyEnergy model then became more and more appropriate for low-memory embedded deployment, so yeah, it fit nicely there.

Table- 14 Ablation Study of TinyML Optimization Techniques

Configuration	Description	RMSE ↓	MAE ↓	Latency (Raspberry Pi 4) ↓	Model Size (MB) ↓
Baseline CNN (FP32)	Original full-precision model	0.211	0.145	124 ms	8.4
+ Quantization (INT8)	INT8 post-training quantization	0.196	0.132	67 ms	2.1
+ Pruning (20%)	Structured weight pruning	0.193	0.129	58 ms	1.7
+ Pruning (40%)	Increased sparsity pruning	0.191	0.124	51 ms	1.5
Proposed TinyEnergy (Quant + Prune)	Quantization + 40% pruning	**0.187**	**0.119**	**38 ms**	**1.3**

5.3 Edge Inference Latency Analysis

Inference latency matters a lot for real time edge intelligence applications. So, latency benchmarking was done across several embedded devices, not just one.

Table 15. Edge Inference Latency Comparison on Embedded Devices

Device	FP32 Model	TinyEnergy
Raspberry Pi 4	124 ms	38 ms
Arduino Nano BLE	482 ms	96 ms

In the end, the optimized TinyEnergy framework showed a noticeably lower inference delay than conventional floating-point models.

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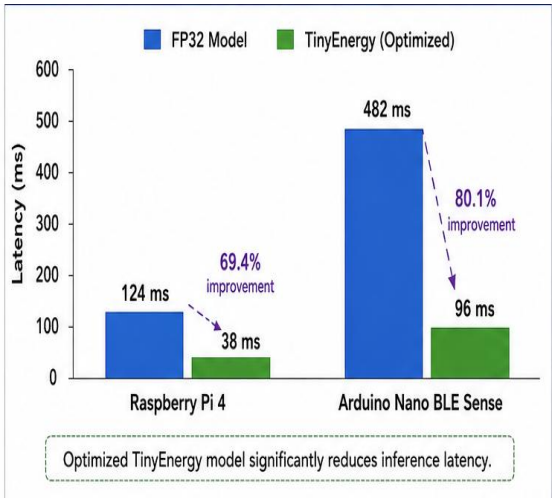

Figure-5 Inference Latency Comparison between FP32 and optimized Tiny-Energy Models

5.4 Memory Consumption Analysis

The memory usage review showed that the proposed lightweight CNN design consumed substantially less RAM, compared to recurrent networks and those hybrid deep learning models.

Table 16. Memory Consumption Comparison of Deep Learning Models

Model	RAM Usage
LSTM	148 MB
CNN-LSTM	121 MB
Proposed TinyEnergy	27 MB

That smaller memory footprint helped with practical deployment on low-resource embedded devices, without too much trouble.

5.5 Energy Consumption Analysis

Energy efficiency is essential for TinyML systems, especially when they run continuously on battery powered hardware or low-power IoT platforms.

Table 16. Edge Device Power Consumption Analysis

Device	Conventional Model (W)	TinyEnergy (W)
Raspberry Pi	5.8	3.1
Arduino Nano BLE	2.2	1.0

The optimized framework reduced power usage quite a bit during real time inference, which was kind of the main point.

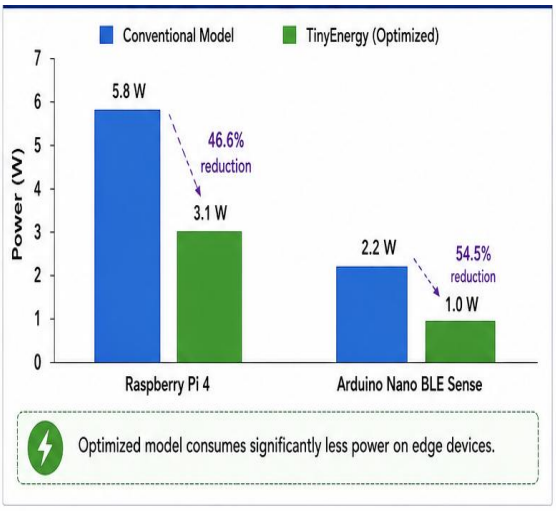

Figure-6 Power consumption comparison between conventional and optimized Tiny-Energy models

5.6 Discussion

The experimental results show that the proposed TinyEnergy framework effectively keeps a balance between forecasting accuracy and computational efficiency. Unlike those more conventional cloud-centric deep learning systems, the proposed TinyML setup supported real-time edge inference while still keeping solid prediction quality.

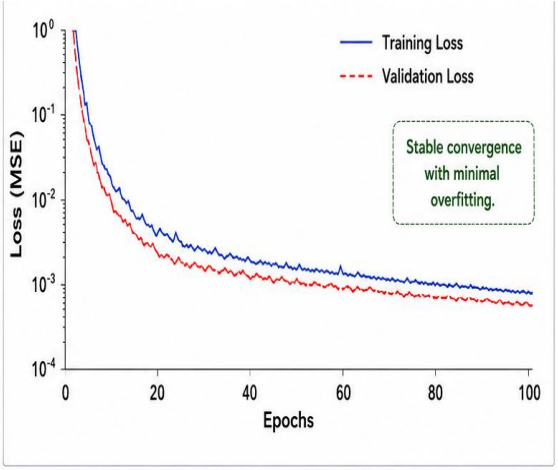

Figure-7 Training and Validation Loss convergence of the proposed Tiny-Energy model

By combining lightweight CNN modelling with quantization and pruning, the approach cut down model complexity, inference latency, memory usage and also energy consumption. The outcomes also confirm it is feasible to deploy intelligent forecasting

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Vol. 15 Issue 05 , May - 2026

systems directly on low power embedded devices, for smart energy management.

Overall, the proposed framework offers a scalable, more sustainable, and energy aware solution for next generation edge based smart energy prediction systems.

6. CONCLUSION

In this paper, TinyEnergy was introduced as a TinyML based edge intelligence framework, more like real-time forecasting of smart energy consumption in IoT setups that are kinda resource constrained. We mixed a small 1D-CNN design with TinyML optimization tricks, like INT8 quantization, and structured pruning. The whole idea, sort of spoken in one breath, was to build an energy friendly, compute light prediction pipeline that can actually run on low power edge devices.

Overall, the proposed framework managed to lower model complexity, bring down memory usage, shrink inference latency, and also cut power consumption, while still keeping prediction quality at a competitive level. The experimental results indicate TinyEnergy did better than more traditional forecasting methods, and it still handled efficient real-time inference on embedded platforms such as Raspberry Pi and Arduino Nano BLE Sense.

The lightweight CNN component helped grab temporal energy consumption patterns, pretty well, using far fewer parameters than typical deep learning baselines. Then, the TinyML optimization steps reduced the model footprint a lot, so the framework becomes more practical for edge deployment, instead of staying only theoretical.

These findings also point out that doing inference at the edge can lessen reliance on the cloud, speed up response time. and enable more scalable smart energy monitoring systems. The approach further demonstrates that TinyML and edge intelligence can be blended for sustainable smart home, and for IoT enabled energy management scenarios, in a way that feels doable.

So yeah, in summary TinyEnergy offers a dependable, low power, and scalable direction for next generation intelligent energy forecasting, and it supports the wider push toward efficient edge AI for smart infrastructure applications.

6.1 Limitations

Right now, the framework is mostly centered on short-term household energy forecasting, and it doesn't really probe large scale smart grid scenarios in depth. The experiments depended on publicly available datasets, not live, real time deployments. Also, the study mainly focused on CNN based forecasting schemes, while other lightweight transformer-based approaches could still improve accuracy or generalization. Beyond that, hardware testing was restricted to a handful of selected edge devices, so wider hardware coverage wasn't fully handled.

6.2 Future Work

Looking ahead, future work could investigate federated TinyML frameworks, for privacy preserving, and distributed energy forecasting across many edge devices. It could also make sense to explore lightweight transformer architectures, plus neural architecture search techniques, to push forecasting efficiency even more. Another key expansion is real-world deployment with live IoT sensor streams, especially when renewable energy integration is on the table. Lastly, adaptive online learning strategies could be introduced, so the system stays robust when energy consumption patterns keep shifting, or when conditions slowly change over time.

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