International Journal of Smart Grid and Clean Energy

The design of a novel smart home control system using a smart grid based on edge and cloud computing

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Abstract

The Internet of Things (IoTs) has transpired as a fascinating technology for smart cities, smart homes, and smart grids using a vast amount of IoT data. A smart grid is one of the core components where transport, generation, delivery, and electricity consumption are enhanced in terms of protection and reliability. The existing power grid is suffering from many problems such as outages and unpredictable power disturbances, inflexible energy rates, unnoticeable customer fraud, and many other disadvantages. These problems lead to the ever-rising demand for fossil fuel and service costs. For example, the peak hour demand needs to be overestimated and more energy generated to minimize the risk of an outage. The main problem of the smart grid is the tremendous amount of data needs to be collected from the IoTs devices, and processing the data is a challenge. Using and predicting a large amount of data in smart Grid and IoTs is still in its infancy. To remedy this problem, we propose a hybrid solution by using the Cloud and Edge Computing to process the data. We define a hybrid solution where we use the edge computing for the smart grid information processing where the microgrids are located on the edge of the IoTs network and on the Cloud to be used for the power grid that distributes power to the microgrids. Additionally, we proposed a machine learning engine to establish the communication between the edge layer, failover between edges, and the Cloud layer.

Keywords: smart grid, edge computing, machine learning

1. Introduction

The Internet of Things (IoT) is an innovative exemplar that provides efficient control services and monitoring [1]. The Internet of Things (IoTs) is a multidisciplinary system that will link many of the surrounding artifacts and things. IoTs are presently a reality where the number of connected devices is growing significantly, for example - cameras, personal electronic devices, medical devices, home appliances, and a wide range of sensors – to the Internet. This universality opens the possibility of advancements that can utilize the information produced by those gadgets to support the foundations of smart infrastructure and services that can enhance personal satisfaction and life quality. Scientists and researchers estimated a significant impact of the IoTs on the global economy [1]. They estimate a possible financial effect of 11 trillion dollars per year by 2025, around eleven percent of the world's economy. They also predict that one trillion IoT devices will be deployed. The leading role of IoT devices in mainstream areas, such as medical services and infrastructure management, is the conveyance of exceptionally complex information-based and action-oriented activities [1]. The Internet of Things offers a different level of applications and services, just as more prominent adaptability for applications and services exists. IoTs, empowered by ongoing advances in remote, detecting, and installed processing innovations, is a new design intended to offer propelled control services and proficient monitoring [1][2]. The scarcity of the standard

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doi: 10.12720/sgce.11.2.57-71

technologies is giving a need for the technology and the research team to make the essential needs of the future generations, better utilization of the energy and use of the energy resources in an efficient way [2]. To achieve this objective, government agencies developed a new project known as "Smart Grid." The primary purpose of this system is to manage the transmission, generation, and distribution of energy efficiently. The stakeholders, such as consumers, distributors, and producers, are allowed to have two-tier communication to effectively generate, consume, and distribute the energy [2].

Buildings, such as offices, structures, and homes, are the major energy consumers, accounting for thirty seven percent of overall energy consumption in developing countries. The manufacturing sector consumes twenty eight percent of total electricity, while the transportation sector consumes thirty-two percent. Because of the lack of a manufacturing sector in developing countries, the proportion is even higher. As a result, energy conservation can be accomplished by making better use of the available energy sources. The goal can be achieved if the energy consumption is measured ahead of time. This knowledge must be transmitted to the local smart grid to achieve the objective of energy conservation [2]. Smart grids will permit clients to get close to ongoing input about their energy utilization and cost, empowering them to settle on their educated spending and utilization choices. From the producer perspective, home utilization information can deliver energy estimates, allowing close to constant response and superior scheduling of energy production and delivery [2][3]. According to existing forecasts, smart grids would save billions of dollars in the long run for both customers and generators [3]. A smart grid is one of the most essential IoTs applications because it improves the security and efficiency of transportation, generation, distribution, and electricity consumption. The current power grid has several issues: inflexible energy rates, unnoticeable customer fraud, unexpected power disturbances, and outages. As a result of these concerns, demand for service costs and fossil fuels is growing. For example, the demand during the peak hours needs to be estimated highly, and more energy is produced to minimize the risk of an outage [3]. Since many end-clients will be participating in procedures and data streams of smart grids, the increase in the versatility of these techniques transforms into a significant matter. To understand these matters, distributed computing administrations present themselves as a practical arrangement by giving dependable, dispersed, and repetitive capacities at a worldwide scale [4].

Nonetheless, a massive pool of functions can't acknowledge the deferral brought about by moving information to the cloud, limited by dormancy. Likewise, it isn't productive to send countless little bundles of information to the cloud for processing. It would drench the network bandwidth with unnecessary processes, which will result in scalability reduction of the applications [5]. In various domains, including the smart grid, smart embedded devices with decision-making capabilities can increase service quality. Like IoTs domains, a smart grid consists of many sensors and data sources that gather high-resolution data on an ongoing basis. Managing the massive volume of data was the critical challenge of IoTs. Traditionally, data processed by IoTs systems, such as smart grids, are relayed back to a primary data centre in the cloud [5]. Since the data centre is located in the cloud, it will take time to travel back and forth from the data centre to the edge devices by putting a significant strain on bandwidth [5]. The smart grid can suffer as a result of this network latency. Edge Computing processes data at the IoTs network's edge to fix this problem, where data is collected near the embedded devices. Edge Computing locates the crucial data to the edge of the network for faster processing allowing them to respond faster and more efficiently [6]. The investigation in this paper focuses on smart homes and demonstrates how to use cloud storage and edge computing for smart grid information processing. A machine learning engine handles the communication and processing between cloud computing and edge processors machines.

In contrast to just using the cloud in the smart grid, the machine learning engine can help us spread the load between the cloud and the edge, helping us achieve a faster processing time. In our proposed approach, the cloud will host the primary grid while the edges will host the microgrids that distribute power to communities. Machine learning is a methodology using which the user feeds an enormous amount of data. The computer algorithm then analyzes and makes data-driven suggestions and decisions based solely on the input data. If any corrections are found, the algorithm will use this knowledge to enhance its performance in future decision-making. There are three sections of machine learning: The analytical algorithm is the heart of decision-making, variables and features that go into making a decision. The system's ability to learn is enabled (trained) by base knowledge for which the response is known. The model is initially fed parameter data for which the answer is already known. The algorithm is then run, with modifications made until the performance (learning) of the algorithm agrees with the known solution. Growing volumes of data are now being fed into the machine to learn and make more complex computational decisions. Data is the lifeblood of all businesses. Data-driven decisions continuously determine whether you stay ahead of the competition or fall further behind. Machine learning can unlock the value of corporate and consumer data and allow companies to make decisions that keep them ahead of the competition.

The concept of supervised machine learning is based on learning by doing. The algorithm is fed data from the problem domain and metadata that assigns a mark to the data. A picture, which is essentially a collection of pixels, and a label are two examples of domain-specific data. This label could mean that the pixels shape a vehicle, a pedestrian, or a significant traffic landmark. Labeling is the process of assigning labels to data, and it's a crucial step in achieving good supervised machine learning performance. It is possible to create a log classifier once the requisite information — log entries and corresponding labels — has been gathered. Classification can be done in various ways, using Linear Support Vector Machines. This classifier requires little preparation and is simple for domain experts to interpret.

2. Background

2.1. Privacy in edge computing

Edge Computing is a game-changing technology that supports various IoTs applications and extends Cloud Computing to the network's edge. Although Edge Computing is advantageous, it may still pose several privacy and security concerns. Edge Computing is compared to Cloud Computing in terms of its underlying definition and functionality. The potential privacy and security threats are being investigated in order to suggest some performance and security criteria. Edge Computing is examined in-depth for advanced secure data analytics. Several problems concerning stable data analytics in Edge Computing have yet to be resolved. Some IoTs applications have a demand and need for real-time response in Edge Computing. The issue of how to balance productivity and security remains unsolved. A very significant number of works require user devices to run certain complex operations that incur enormous costs for computing. Complex computing affects performance, in particular, for consumer devices whose resources are constrained. As a result, in many real-world situations, a tradeoff between productivity and security becomes necessary.

Edge Computing makes it difficult to ensure processing, analytics, and computing data because neither edge nodes nor cloud servers can be completely trusted. When performing data analytics with edge nodes, there is no feasible way to test data accuracy. When it comes to outsourced data analysis, the accuracy of calculation is still paramount. End-users would be unable to use Edge Computing technology if no security solution was available to ensure accuracy. Edge Computing becomes the major issue in achieving robust and stable data analytics by classifying end-user data sensitivity and managing those files. Some are required, such as geographic data and health status, while others are not, such as climate-related data and social events.

2.2. Cloud computing

Cloud Computing advantages are well-known in the business world and wouldn't have many services that businesses of all sizes rely on today if it weren't for it. As a result, it's no surprise that 85 percent of businesses believe cloud adoption is essential for innovation. However, during the current Covid-19 crisis, that cloud has truly come into its own, allowing millions of businesses worldwide to continue operating while virtually all of their employees' login from home. Data is accessed remotely at an increasing rate as more people work away from the office [7]. Remote access is becoming more common, giving cyber criminals more opportunities to access company data and misuse the information contained therein. Instead of sending data to a central data center, data is filtered and processed locally before being sent to the organization's network core via the cloud. If sensitive data is transferred less frequently between devices and the cloud, businesses and their customers will benefit from increased security.

2.3. Machine learning in edge computing

Machine learning models have not been widely used due to a lack of training data and computing power. On the other hand, machine learning can now be realized thanks to increased computing power and a large amount of data available to train machine learning algorithms. The main approach for improving customer service efficiency on future generation networks is to cache most known content close to user devices, i.e., at edge nodes. However, accurately forecasting the popularity of the content and determining which content needs to be stored in the server's cache is difficult. The popularity of content is predicted and learned using machine learning algorithms. Edge nodes provide access to a community of close friends who share common content interests. Lower latencies are achieved by caching common data on edge nodes while lowering the load on core networks. Social and temporal characteristics of content, such as likes and the number of people who watched, are used to assess the success of content from a global perspective.

User flexibility, aspirations, and content popularity are the most prominent dynamic characteristics of edge networks. Edge networks can use machine learning approaches to predict content popularity based on end-user expectations, substitution strategies, associated content interests, and cache replacement optimization. With advances in computing power and big data, they were able to achieve high prediction accuracy. Machine learning models are trained and used in the cloud data centre to make an effective cache decision. The decision is then sent to each server in order to store the typical content in advance. With advances in computing power and big data, they were able to achieve high prediction accuracy. Machine learning models are trained and used in the cloud data centre to make an effective cache decision. The decision is then sent to each server to store the typical content in advance. The term "cache" refers to in-network storage that holds the contents of frequently requested data. Over the last decade, edge networks have used network caching to address high content latency problems while reducing the burden on backhaul networks. Clustering, grouping, forecast, and machine learning methods are useful for clustering, grouping, and prediction tasks. Machine learning (ML) allows computers to learn from their past experiences without having to program them explicitly. The dataset on which the algorithms trained themselves is the experience in this case. The dataset's models will uncover the underlying trends and patterns over time.

Machine learning is a methodology using which the user feeds an enormous amount of data. The computer algorithm then analyses and makes data-driven suggestions and decisions based solely on the input data. If any corrections are found, the algorithm will use this knowledge to enhance its performance in future decision-making. There are three sections of machine learning: The analytical algorithm is the heart of decision-making, Variables and features that go into making a decision. The system's ability to learn is enabled (trained) by base knowledge for which the response is known. The model is initially fed parameter data for which the answer is already known. The algorithm is then run, with modifications made until the performance (learning) of the algorithm agrees with the known solution. Growing volumes of data are now being fed into the machine to learn and make more complex computational decisions. Data is the lifeblood of all businesses. Data-driven decisions continuously determine whether you stay ahead of the competition or fall further behind. Machine learning can unlock the value of corporate and consumer data and allow companies to make decisions that keep them ahead of the competition. The concept of supervised machine learning is based on learning by doing. The algorithm is fed data from the problem domain and metadata that assigns a mark to the data. A picture, which is essentially a collection of pixels, and a label are two examples of domain-specific data. This label could mean that the pixels shape a vehicle, a pedestrian, or a significant traffic landmark. Labelling is the process of assigning labels to data, and it's a crucial step in achieving good supervised machine learning performance. It is possible to create a log classifier once the requisite information — log entries and corresponding labels — has been gathered. Classification can be done in various ways, using Linear Support Vector Machines. This classifier requires little preparation and is simple for domain experts to interpret.

The three major categories of algorithms used in Machine Learning: Reinforcement Learning, Unsupervised Learning, Supervised Learning. To create a function that maps inputs to desired outputs using this set of variables. On the training data, the model is trained until it achieves the desired level of accuracy. Decision Tree, Regression, Random Forest, Logistic Regression, KNN, and others are supervised learning examples. There is no objective or outcome attribute to estimate or predict unsupervised learning algorithms. It is commonly used for segmenting consumers into different groups for particular interference, and it is used for clustering populations into other groups. A prior algorithm and K-means are two examples of unsupervised learning. The computer is taught to make particular decisions using the Reinforcement Learning algorithm. It works like this: the system is placed in an environment where it must continuously train itself through trial and error. This computer learns from its previous experiences and records the most relevant information to make correct decisions. Markov's Decision Process is an example of Reinforcement Learning.

2.4. Deep learning

Deep-learning architectures like convolutional neural networks, deep belief networks, deep neural networks, and recurrent neural networks are used in fields like machine vision, computer vision, natural language processing, social network filtering, drug design, material inspection, bioinformatics, medical image analysis, and among others. This technique is an AI function that involves processing data and creating patterns to make decisions. Deep learning is a branch of artificial intelligence that employs neural networks to learn unsupervised from unlabeled data or unstructured data. Deep learning has evolved in lockstep with the modern age, resulting in an explosion of data in all types and from all corners of the globe. Internet search engines, social networking, online cinemas, and e-commerce websites are examples of where big data can be found. This enormous volume of data is easily accessible and can be shared using fintech resources like cloud computing. However, since unstructured data is common, humans can take decades to understand and extract relevant information.

For example, A deep learning example can be created by combining the fraud detection method described above with machine learning. The machine learning system builds a model with parameters based on the amount of money a user sends or receives. Each layer of the neural network adds additional data to the previous layer, such as a shop, user, sender, credit score, social media event, IP address, and a slew of other features that, if processed by a human, may take years to communicate. Deep learning algorithms are trained to produce patterns from all transactions and identify when a pattern suggests the need for a fraud investigation. The final layer sends a signal to an analyst, who may decide to put the user's account on hold before all open investigations are completed. Deep learning is used in a range of industries for a variety of tasks. Deep learning is being used in commercial applications that use open-source systems, image recognition with medical research tools, and user recommendation apps that look at the possibilities of reusing medications for new diseases, to name a few examples.

3. The Problem Statement

The Internet of Things (IoTs) has transpired as a fascinating technology for smart cities, smart homes, and smart grids. A smart grid plays a vital role in different IoT applications like consumption, delivery, transport, and generation of electricity are enhanced in terms of protection and reliability. The current power grid has many issues, including inflexible energy rates, unnoticeable customer fraud, unexpected power disturbances, and outages. As a result of these concerns, demand for service costs and fossil fuels is growing.

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The key issue with the smart grid is the massive amount of data obtained from IoTs devices and handling this massive amount of data is considered a difficult task. Controlling a massive amount of data in IoT and Smart Grid is still in its infancy. To remedy this problem, a hybrid architecture is proposed for the smart grid focusing on smart homes that consist of hybrid technologies: edge computing, cloud computing, and machine learning. This machine learning model analyses the historical data usage of energy and then accordingly provides energy to the users. A Machine learning engine is proposed that establishes the communication between the cloud layer and the edge layer and analyses the impact of increasing the edge nodes on power utilization and the system throughput.

4. The Proposed Architecture and Energy Management Plan

4.1. The architecture

The architecture of the smart grid using the edge and the cloud computing can be described as a composition of two layers. The first layer consists of the cloud, and the second layer consists of an array of *n* edge servers. The architecture is represented in Fig. 1. The cloud layer consists of the primary grid that distributes power to the microgrids in the edge layer. The edge layers consist of n edges, and each one of these edges has m numbers of microgrids. The microgrid is defined as interconnected subgroups of low-voltage electricity networks. The microgrid can improve the efficiency of local delivery by providing controlling mechanisms and self-generating [12]. It can be connected with the power grid but can also isolate itself from it, and this mode can be known as the island.

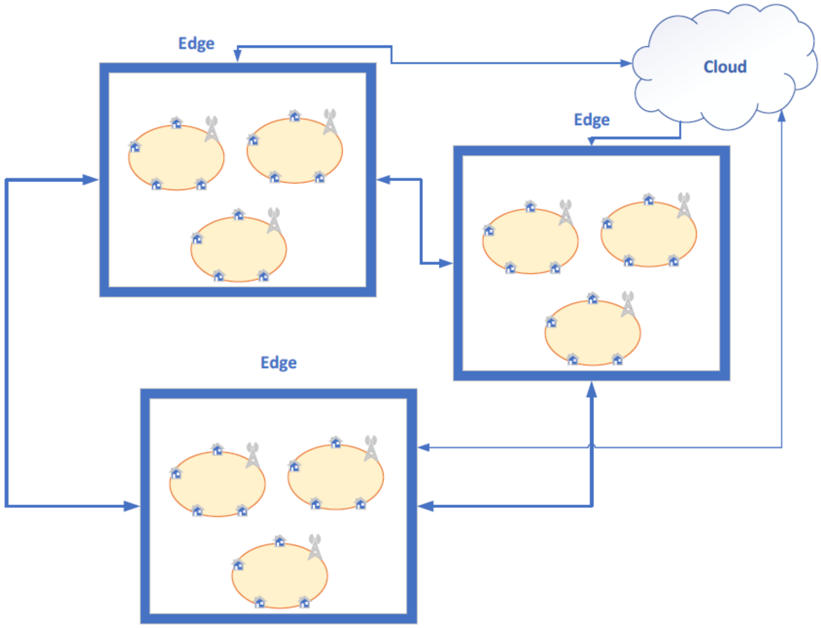

Fig. 1. The architectural design of the smart grid that consists of cloud computing and edge computing

This action takes place when there is a grid fault, malfunction, interference, or other danger. The proposed architecture provides a model for smart homes for the smart grid. The primary grid is located in the cloud and will distribute power to the microgrids on each edge. A machine learning engine is designed. This engine will be placed as a combination of two modules. As shown in Fig. 2, one module will be located in the edge layer close to the consumer, and in this case, the consumer is the smart home. The other module will be placed in the cloud where the primary grid is located. The machine learning engine will be fed historical usage data, along with peaks level, peak hours, usage per consumer, or each edge area along with other business rules, including business areas versus residential or mixed, etc. The decision will be placed on providing power to the edge and failover to other edges in case an edge reached the peak value. Furthermore, contact with the cloud will continue to choose to send more power to an edge than to other edges, rather than the edge receiving additional power from linked edges. The model for connected edges will be based on proximity and various categories specified by the power company.

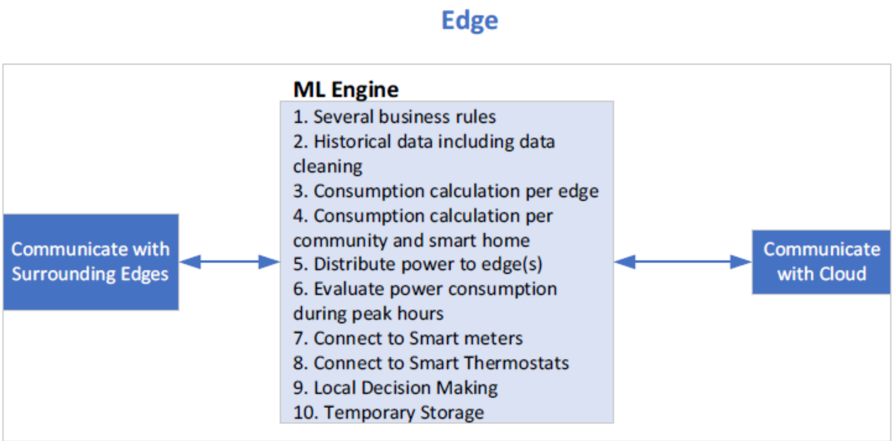

Fig. 2. The machine learning engine communication with the edge layer and cloud layer

4.2. Machine learning module

The machine learning engine is used to analyze the historical data and predict the future usage of smart homes. Supervised classification is used in the machine learning engine to use energy usage information for each smart home and predict future usage. The machine learning module that is located at the edge layer predicts the usage of the smart homes connected to the microgrids on each edge. Based on that information, a smart grid market is applied where power can be transformed between edges. For example, if the smart home in one edge does not use the assigned power from the primary grid located in the cloud.

The remaining power can be transformed to other edges which need the power based on the utilization of the microgrids in each edge. Besides, based on the utilization of the microgrids, the cloud can distribute power to the edges based on the needs which are obtained from the machine learning module at the edge layers. The machine learning algorithm that is used in this module is Long Short- Term Memory in Recurrent Neural Network LSTM- RNN, which is also an Artificial Intelligence Technique.

Recurrent Neural Networks (RNNs) can extract sequences and long-term patterns from continuous sequential data [12]. These networks are widely used in Audio Data Processing, Natural Language Processing, Time-Series Data Analysis, and other applications [12]. Finding hyperparameters for any deep learning network is important. These are used to fine-tune the learning model. The only hyperparameters that RNNs need are the number of nodes in each layer, the number of hidden layers, and the optimizer for training the network. RNNs are one of the most modern neural classes and most popular, with the ability to retain data. However, due to its short memory, it suffers from vanishing gradients. Gradients are the values that are used to change the 13weights of neural networks. Gradient shrinks as RNN back propagates over time, and If the gradient value is too low, it will be unable to contribute as much to learning. The LSTM model is used to provide a solution to this problem in RNN.

Long-Short Term Memory (LSTM) is a common RNN variant that is frequently used in the sense of time series data [13]. With the aid of its cell mechanisms and Gating, it maintains the network's long-term dependencies. Through the gating mechanism, the LSTM network will store and release memory on the fly. It tries to model behaviour that is sequence or time based, such as stock prices, electricity demand, and language, among other things. In the sense of Smart Grid and LSTM, authors in [13] emphasized the use of LSTM to analyse large quantities of energy data. Similarly, in [13], the authors proposed an RNN-based LSTM model for analysing smart grid time series data. They also brought up a range of issues relating to grid knowledge, such as short-term energy demand forecasting at the user

5. The Characteristics of Edge Server, Cloud Computing, and Microgrid

5.1. The edge servers

The use of big data and cloud computing is increasingly increasing [13]. More data collectors and nodes than ever before are sending data to the cloud. People are discovering that sending unfiltered data to the cloud is dangerous. Both the cost of storing the data and the cost of transmitting it will be paid. You want to hold only the data that you need and need. As a result, making your computational decisions ahead of time before sending it up would save you money on both transmission and cloud fees. They necessitate processing on the spot. And that's how it came into being. Artificial intelligence, deep learning, and computer vision are currently being researched, but Edge Servers are the next move. As a result, many analytics and tasks that must be completed are now taking place outside of data centers.

They are high-performance machines located at the network's edge where data processing is needed. They are similar to machines or programs that create data that is stored on the server or used by it. The Edge Server will perform a lot of the necessary computation right at the edge. As technology has advanced, decision-making must be made quickly. If a decision can't be taken right away, it can have serious implications, especially with the rise of artificial intelligence.

The Edge Server needs connectivity because it must connect to the intranet or the cloud to transmit data until all of the information has been generated, sorted, and responded to. It's a more cost-effective method of data management. Getting more data processed there, on the other hand, isn't going to help. As a consequence, you'll need to find out what's needed; this is where Edge Servers will help. The more powerful computers are needed to make it more understandable and accomplish that, the better the industry becomes.

5.2. Cloud computing

Data is being accessed remotely at an increasing rate as more people work away from the office. Remote access is becoming more common, giving cyber criminals more opportunities to access company data and misuse the information contained therein. Instead of sending data to a central data center, data is filtered and processed locally before being sent to the organization's network core via the cloud. If sensitive data is transferred less frequently between devices and the cloud, businesses and their customers will benefit from increased security.

5.3. Microgrids

Micro-grids are a form of the low-voltage electricity system that is made up of interconnected subgroups. Microgrids can improve the efficiency of local delivery by having self-generating and management mechanisms. A micro-grid can be linked to the power grid but can disconnect (go into island mode) when the grid experiences a fault, malfunction, interference, or other danger. Buildings, such as offices, structures, and homes, are the major energy consumers, accounting for thirty seven percent of overall energy consumption in developing countries. The manufacturing sector consumes twenty eight percent of total electricity, while the transportation sector consumes thirty two percent. Because of the lack of a manufacturing sector in developing countries, the proportion is even higher. As a result, energy conservation can be accomplished by making better use of the available energy sources. The goal can be achieved if the energy consumption is measured ahead of time. This knowledge must be transmitted to the local smart grid in order to achieve the objective of energy conservation [13].

6. The Deep Learning Proposed Engine

To evaluate the energy usage of smart houses, an RNN-LSTM based deep learning model is proposed, which can be used to predict future consumptions with the fewest errors and highest accuracy. The pre-processed Smart Grid data is processed and analyzed using an RNN-LSTM based algorithm in this scheme shown below in Fig. 3.

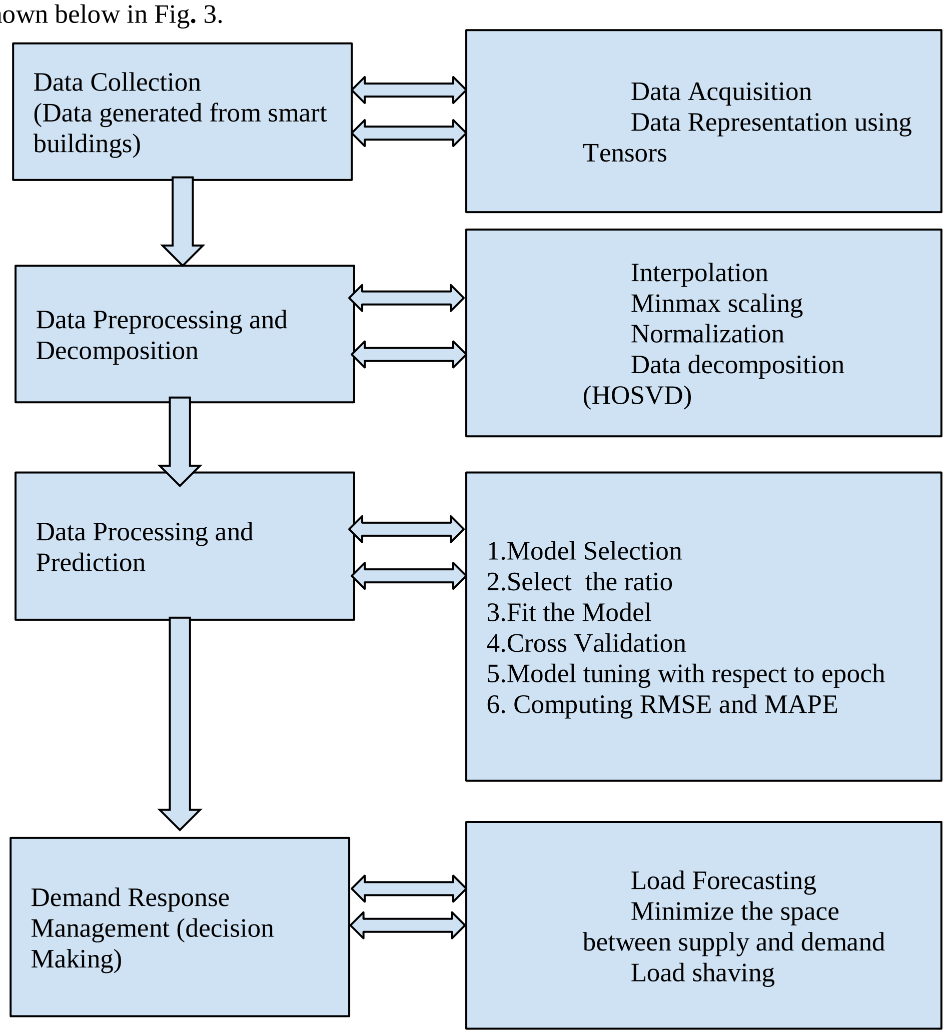

Fig. 3. The machine learning engine schema diagram

6.1. Data collection

Smart Grid systems collect data on energy usage, occupancy patterns, and end-user movements on a daily basis from various electrical appliances and smart devices are installed in smart buildings. Data is generated from a variety of sources, including smart homes, substations, grid utilities, and industries. The key data generation sources in Smart Grid systems are Advanced Metering Infrastructure (AMI) and Phasor Measurement Units (PMU). As shown in equation 2, D_{ac} is defined using tensor models. The different characteristics and dimensions of big data are effectively used to represent the tensors that are multi-dimensional arrays. The following equation can be used to describe a tensor (T) of order n:

$$\mathrm{T} \in \mathrm{R}a1 \times a2 \times a3 \ldots \ldots.. \times an. \tag{1}$$

$$Dac \rightarrow Tac \tag{2}$$

The energy measurement units in Smart Grid are called PMUs, and they measure energy waves and signals. AMIs, on the other hand, are smart meter and sensor integrations with advanced two-way communication infrastructure. Data from AMI, which is very large in quantity and difficult to manage, can be produced hourly or even for shorter periods of time. According to the National Institute of Standards and Technology's (NIST) Smart Grid structure, bulk data generation, data processing, and improved service provisioning to end users are the key tasks that need to be performed in Smart Grid systems, according to the National Institute of Standards and Technology's (NIST) Smart Grid structure.

6.2. Data preprocessing

Since it has the essential big data characteristics of length, velocity, and veracity, the bulk of data produced in Smart Grid systems can be classified as big data. An advanced data pre-processing and analysis methodology is needed to deal with such a large volume of data. When it comes to data pre-processing, the first step is to represent the data using an efficient and effective model. Data pre-processing is performed after data representation, in which T_{ac} is washed, normalized, and minmax scaled. Since one of the most critical steps of data pre-processing is dimensionality reduction, HOSVD is used on T_{ac} to obtain the reduced core tensor (T_{red}).

As shown in the following equation, the core tensor is obtained by the n-mode product of the n-order tensor (T_{ac}) with the orthogonal matrix (U).

$$Tred = Tac \times n\, x = 1\, UT\, n \tag{3}$$

The tensor model is one of the viable solutions for efficiently representing multidimensional big data. After the representation, data must be pre-processed, which involves data normalization, eliminating null and duplicate values, minimizing dimensionality, etc. One of the most important steps in the data pre-processing process, dimensionality reduction or data decomposition, has a huge effect on data processing. Further, using the following equation, ($\hat{T}_{red}$) is an approximated tensor which is rebuilt from the core tensor to verify the rebuilt error:

$$T\hat{}\, red = Tred \times n\, x = 1\, UT\, n \tag{4}$$

The rebuilt error (e) is used to measure the approximation error of the reduced core tensor:

$$e = |Tac - T\hat{}\, red| \tag{5}$$

As a consequence, lowering the reconstruction error is one of the proposed scheme's goals. It is defined using the equation below.

$$min(e) \tag{6}$$

$$e = [0,1] \tag{7}$$

$$s.t. \tag{8}$$

$$T_{ac} > \hat{T}_{red} \tag{9}$$

$$T_{ac}, \hat{T}_{red} > 0 \tag{10}$$

Various authors have proposed different methods for dealing with big data decomposition in the form of tensors and smart grids. HOSVD, on the other hand, is an efficient technique for representing high-dimensional data in lower dimensions with the least amount of reconstruction error. To process the reduced data, the RNN 's hidden layer (h_t) receives the core tensor as an input. The activation feature is used to trigger the hidden layer. In the context of neural networks, different activation functions, such as the sigmoid and tan (h) functions, are available. RNN, on the other hand, fires h_t using a rectified linear unit (ReLu). ReLu is non-linear in nature and avoids vanishing gradients to some extent. The following equation is used to describe it mathematically:

$$h_t\,(rnn) = \theta\,(u * x_t + w * h_{t-1}) \tag{11}$$

Where θ represents ReLu as an activation function. The following is the mathematical equation for the formula θ:

$$f(z) = max(0, z) \tag{12}$$

$$s.t. \tag{13}$$

$$\theta = [0, \infty) \tag{14}$$

6.3. Data prediction

The problem of vanishing or exploding gradients is common in recurrent neural networks. As a result, the data is trained and tested using the LSTM model. Since it can maintain memory for longer periods, the LSTM model is a solution to the vanishing gradient problem in neural networks. Its gating function filters out meaningless data, leaving only the most significant data to be passed on. The RMSE score and MAPE values (ρ) of the regression model are used as objective functions to test the model. The corresponding mathematical equations are shown below.

$$\epsilon = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\big(Ypred(i) - Yact(i)\big)2} \tag{15}$$

$$\rho = 1/n \sum_{i=1}^{n} \text{ypre(i)} - \text{yact}, \text{(i)}/\text{yact(i)} \tag{16}$$

6.4. Demand response management

Where $Y_{pred(i)}$ and $Y_{act(i)}$ are the predicted and actual values at the i^{th} instance of data. So, the main objective function of the proposed scheme is to minimize the error in prediction values. It is represented by the following equation:

$$min(\in), min(\rho) \tag{17}$$

$$s.t. \tag{18}$$

$$0 \geq \rho \leq 1 \tag{19}$$

$$\rho = [0,1] \tag{20}$$

7. The Proposed Algorithm

Big data from the Smart Grid is collected and fed into the proposed algorithm as input. After that, it is interpreted using data pre-processing, and tensors are applied to it (line 1-2). It's also decomposed, and a reduced core tensor is obtained (line 2-6). The data is then fed into the LSTM model. The testing and training ratio is chosen, and the model is built (7-9). Then, to process the data, a hidden state (ht) is obtained and passed to the next LSTM cell at (t+1). The model is iterated for a set number of epochs until the threshold is reached. The RMSE score and MAPE are calculated along with the predicted values for data. Fig. 4 explains the flow of the algorithm.

1 RNN-LSTM based data analytics algorithm
Input: Dac (Acquired high dimensional Smart Grid big data)
Output: Epre, Ei total

1. Initial step is to represent D_{ac} which uses tensors using eq(1).
2. Data cleaning is performed.
3. Perform scaling and normalization.
4. Higher Order Singular Value Decomposition(HOSVD) is applied on T_{ac} using eq(2).
5. To calculate the reconstruction error (e) using eq (4)
6. To Minimize the e using constraints eq (5) - (9)
7. T_{red} is taken as input to RNN-LSTM , eq (10)
8. Train: Test data is selected
9. Combine current input and the previous hidden state (h_{t-1})
10. **For** (i=0; i <= epoch; i++) **do**
11. Do the model iteration
12. Perform BPTT
13. E_{pre} is obtained in this step
14. Calculate E, p using eq (15) and (16)
15. Minimize E, p using eq (19) - (21)
16. Forecast E_{total}^{i} is used calculate the final output.

Fig. 4. The proposed algorithm

8. Performance Evaluation

A testbed is created to evaluate the proposed architecture's results. For the edge layers, six Raspberry PI of size 2 GB are used that are connected using wireless Internet. So that six edge nodes are used where each node is a complete Linux machine. Table 1 shows the configuration parameters for the edge nodes used in our implementation.

1. Initial step is to represent D_{ac} which uses tensors using eq(1).
2. Data cleaning is performed.
3. Perform scaling and normalization.
4. Higher Order Singular Value Decomposition(HOSVD) is applied on T_{ac} using eq(2).
5. To calculate the reconstruction error (e) using eq (4)
6. To Minimize the e using constraints eq (5) - (9)
7. T_{red} is taken as input to RNN-LSTM , eq (10)
8. Train: Test data is selected
9. Combine current input and the previous hidden state (h_{t-1})
10. **For** (i=0; i <= epoch; i++) **do**
11. Do the model iteration
12. Perform BPTT
13. E_{pre} is obtained in this step
14. Calculate E, p using eq (15) and (16)
15. Minimize E, p using eq (19) - (21)
16. Forecast E_{total}^{i} is used calculate the final output.

Table 1. Edge node configurations

Parameter	Specification
Edge node numbers	6
Hardware for the Edge Nodes	Raspberry pi 2 B
RAM	1 GB
Processor	900 MHZ Quad Core

The board of the Raspberry Pi board has a 1Gbps network capability, multiple I/O options that have HDMI, and features like nodes power management via a 12C bus. The Raspberry pi platform is used to develop and host IoT applications locally or at the edge.

For the cloud layer, a set of virtual machines on Microsoft Azure are created that can communicate with the edge layer using wireless technology. For wireless technology, Zigbee wireless technology is used. The cloud layer receives information from multi-edge nodes simultaneously. It also can send data to more than one edge node concurrently.

8.1. The impact of edge nodes on power utilization

In this section, our architecture is compared with another strategy called the cloud; in this strategy, the smart grid is connected to the cloud only. To stringently evaluate our proposed approach and the competitive strategy. The number of edges in the edge layer is increased from 2 nodes to 8 nodes, and then tested this change on the utilization of power. The power utilization is defined as the following equation

$$Pu = \frac{Assigned - (no * massigned)}{assigned} \tag{22}$$

Where

Pu: the power utilization

Assigned: the power assigned to the edge in Kilowatts

No: the power assigned to each community in the edge,
assigned to the microgrid.

EXAMPLE

1. Fig. 5 below shows that if the power assigned for one edge is 1000KW, each community in the edge is assigned 100KW and has five communities per edge where each community is assigned to a microgrid. Then the utilization is (1000-(5*100))/1000= 50%

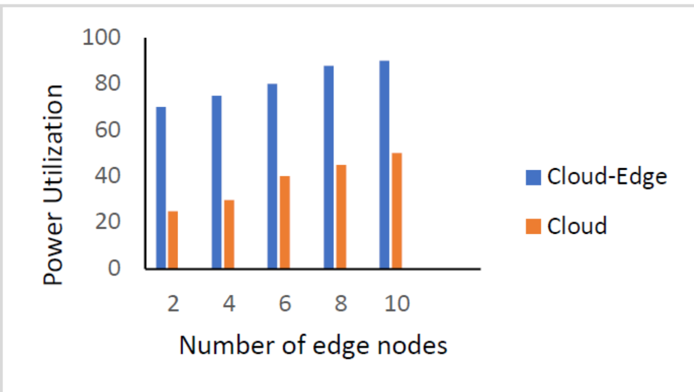

Fig. 5. The impact of edge nodes on power utilization

Fig. 6 below shows that if the power assigned for one edge is 2000KW, each community in the edge is assigned 200KW and has five communities per edge where each community is assigned to a microgrid. Then the utilization is (2000-(2*200))/2000= 80% .

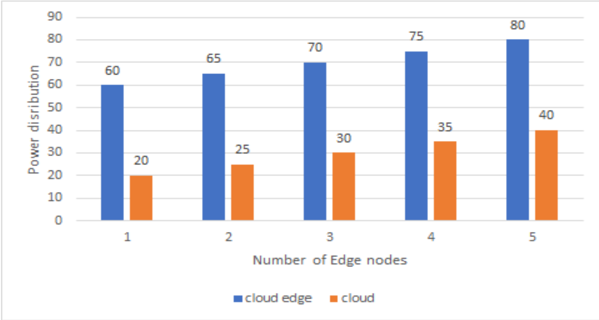

Fig. 6. The impact of edge nodes on power utilization

8.2. The impact of edge nodes on the system throughput

In this experiment, the impact of edge nodes on the throughput is tested. In our experiments, as is shown in Fig. 7, I looked at how our testbed application behaved when processing data between the cloud and the edges and compared it to how it behaved when data was processed in the cloud. In this way, more data can be handled at the edge and reduce the load on the cloud; thus, it would increase the overall throughput.

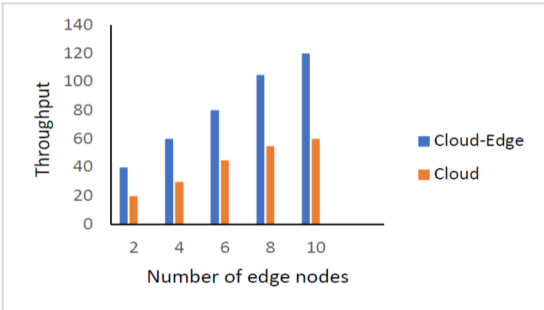

Fig. 7. The impact of edge nodes on throughput

The simulation results obtained by applying the proposed mechanism to energy related data produced by smart homes are presented in this section.

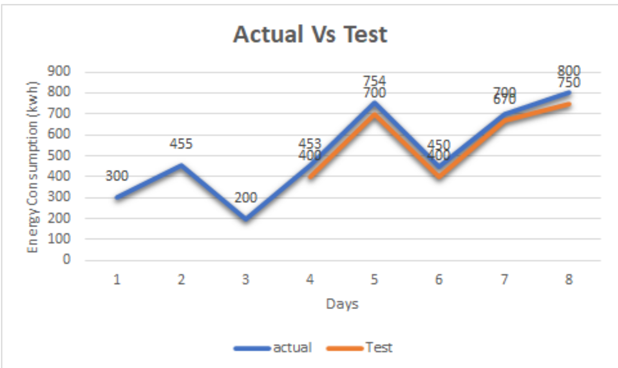

Fig. 8. Actual data Vs test data

Fig. 8 shows measuring the energy-consumption in kilowatt per hour (kwh) for 10 days at a half-hour sampling rate for each home. Different environmental variables, such as cloud cover, temperature, visibility, wind bearing, wind speed, pressure, and so on, are taken into account during the study. Data on energy consumption and weather conditions are combined, then pre-processed and decomposed.

9. Conclusion

A smart grid is one of the most important IoTs applications because it improves the security and efficiency of transportation, distribution, generation, and electricity consumption. Many issues challenge the existing power grid include outages, inflexible electricity prices, intermittent power disruptions, and undetected consumer fraud. As a result of these concerns, demand for fossil fuels and service costs are growing. For example, the demand for peak hours needs to be excessively optimistic, and more energy is generated to minimize the risk of an outage. In this thesis, a hybrid platform has been used that would include edge computing, cloud computing, and machine learning to incorporate smart home's intelligent grid framework. Our proposed model was able to achieve higher throughput and higher power utilization.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

Dr. Mais Nijim conducted the research, designed the framework, and the machine learning algorithm, and wrote the paper.

Divya Ballampali implemented the whole system and the machine learning algorithm, wrote the performance evaluation section.

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