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POWER CONSUMPTION PREDECTION

MS. J.Maheswari [a] ,K.Sambath [b] ,R.Venkatesh [c] ,M.Venu Aravind [d] ,C.Vignesh [e]

[a] Assistant Professor Faculty of Engineering and Computer Science, Dhirajlal Gandhi College of Technology, India. Students in the Department of Computer Science and Engineering, b, c, d, e ,Dhirajlal Gandhi College of Technology, India.

ABSTRACT:

By offering a wide range of intelligent services, including intelligent energy and transportation, smart cities can improve our everyday lives. One of the most often used energy sources is electricity. The task of taking readings to ascertain the final consumer's energy consumption is currently the responsibility of the electrical distribution companies. Field personnel contractors carry out this task, which exposes them to threats to their physical integrity due to social and climatic conditions. When residential building owners get their monthly electric energy bill, the data does not distinguish between household loads and appliance usage patterns. Customers might take steps to significantly reduce the electrical energy consumption of devices if they could recognise those with greater consumption based on history and baseline use.

1. INTRODUCTION

In the beginning, the phrase "smart meter" referred to devices that could measure the amount of electricity generated or consumed as well as remotely manage the supply and turn it off when needed. Using one-way communication, it was known as AMR and was able to perform simple load profiling, one-way outage (or last gasp) and tamper detection, and automated monthly scans. As time went on, the AMR capability was expanded to link to and read additional commodities at short intervals (hourly or less). The meters' integration with two-way communication technology, known as advanced metering integrated (AMI), resulted in a significant improvement in functionality. Service switching, time-based pricing, remote programming, power quality monitoring, and a dashboard-style user interface for real-time consumption tracking were all incorporated in the upgrade.

LITERATURE SURVEY

2.1. Using time series modelling to forecast short-term loads with the ability to estimate peak loads, IEEE Transactions on Power Systems, Vol.16, No.3, August 2001

Analysis of time series: Time series analysis uses the succession of data, usually at equal intervals. This approach makes predictions about the future based on historical data and aims to comprehend data patterns. For a brief time in the future, TSA is frequently utilised.

2.2. Transactions on Power Engineering, vol. 6, pp. 442-449 (1991), "Electric load forecasting using an artificial neural network" by D.C. Park, M.A. El-Sharkawi, R.J. Marks II, L.E. Atlas, and M.J. Damborg

Artificial Neural Network: An artificial neural network (ANN) is a soft approach utilised in many optimisation procedures. Nonlinear modelling and adaptation can be done with this approach. There is no need to presuppose that load and weather factors have any functional relationship. By exposing the ANN to fresh data, we can modify it. Other power system issues like security evaluation, harmonic load detection, alarm processing, fault diagnosis, and topological observability are also being studied with the ANN as a potential tool.

2.3"Power System Topological Observability Analysis Using a Neural Network Model," Proceedings of the 2nd Symposium on Expert Systems Application to Power Systems, pp. 385-391, July 1989, H. Mori and S. Tsuzuki

Expert System: A computer software that can function as an expert is called an expert system. This implies that as new information becomes accessible to the computer program, it may reason, explain, and grow its knowledge base. An expert in the field's knowledge of the load forecast domain is used to build the load forecast model. The "Knowledge Engineer" retrieves this information from the load forecast (domain) expert, which is referred to as the expert system's acquisition module component.

2.4. M. S. Kandil, S. M. El-Debeiky, Senior IEEE Member, and N. E. Hasanien, Knowledge-Based Expert System-Based Long-Term Load Forecasting for Rapidly Developing Utility.

Fuzzy reasoning: In some ways, fuzzy logic is similar to Boolean logic, where the input can be the truth value expressed as "0" or "1." In fuzzy logic, however, the input is connected to a comparison based on attributes. Mathematical models are not required in fuzzy logic to map inputs to outputs. It does not require accurate or even noise-free inputs, and it is not impacted by noise (error). To obtain the precise results, "defuzzification" is carried out after the entire processing is completed using fuzzy logic.

2.5. Mohamed Mohandes, Short-term electrical load forecasting using support vector machines Energy Research International Journal Int. J. Energy Res. 2002; 26:335-345 10.1002/er.787 (DOI)

Vector machines for support: The most potent and modern method for resolving regression and classification issues is Support Vector Machines (SVM). In support vector machines, linear decision boundaries are established in the new space using linear functions. The choice of architecture is the issue with neural networks, while selecting an appropriate kernel is the issue with support vector machines.

2.6A general formulation for support vector machines by Wei C3hu, S. Sathiya Keerthi, and Chong Jin Ong, Proceedings of the 9th International Conference on Neural Information Processing (ICONIP'OZ), Vol. 5

Time component: Since SLTF is done on an hourly basis, time is the most important factor in the case of STLF for accurate load forecasting. As seen in Figure (1), the Sri Lankan government has produced a report that includes a load demand curve. Demand peaked at 18 HRS, as seen by the curve. Therefore, a uniform analysis is insufficient for load forecasting. Good forecasting will come from careful hourly load monitoring. Additionally, there are significant differences in load at the same time in the summer and winter. Seasonal variations cause some changes in the load pattern to happen gradually.

3.1. EXISTING SYSTEM

Traditional machine learning method Support Vector Machine (SVM), k nearest neighbour (KNN), random forest (RF), extreme random forest (ERF), Support Vector Regression (SVR), Artificial Neural Network (ANN), Autoregressive Integrated Moving Average (AIMA), and Multiple Linear Regression (MLR) are the eight conventional machine learning techniques used to construct household appliance energy consumption prediction models.

- SVM stands for Support Vector Machine.
  SVM is a type of generalised linear classifier used in supervised learning for binary data classification.
  Nearest Neighbour (KNN-K)
- KNN can be used for regression by identifying a sample's closest neighbours and calculating the sample's properties by averaging the characteristics of these neighbours. Giving varying weights to the impact of neighbours with varying distances on the sample—for example, the weight being inversely proportional to the distance—is another enhanced technique.
- Random Forest (RF)
  Regression and classification can be accomplished with RF, a significant bagging-based integrated learning technique. A random forest regression model is used in this work.

3.1.1. DISADVANTAGES

The extra expense of hiring staff, creating tools, and putting new data storage procedures into place; controlling public opinion and feedback regarding new meters; committing financially over the long term to new hardware and software; and guaranteeing the security and privacy of metering data.

3.2. PROPOSED SYSTEM

In order to produce forecasts with high accuracy and low error percentages in comparison to the aforementioned models, a hybrid model (HSBUFC) is developed in this project. It is based on the stacking of bi-directional and uni-directional LSTMs followed by fully linked dense layers. The unidirectional and bidirectional LSTM architectures are examined. Using previous and upcoming inputs, bi-directional LSTMs use forward and backward passes to identify innate patterns in energy usage data.

3.2.1. ADVANTAGES

- Precise monthly household electricity consumption predictions for effective power-system design.
- Accurate demand forecasts improve decision-making for market participants and electricity system staff.
- Use of the deep learning model for sustainability, energy optimisation, and time series analysis

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4.1 HARDWARE REQUIREMENTS

- **Processor :** Multi-core processor (e.g., Intel Core i5 or higher)
- **RAM :** Minimum 8GB RAM, recommended 16GB or more
- **Storage :** Minimum 500GB HDD or SSD

4.2. SOFTWARE REQUIREMENTS

- **Operating System** : Windows 10 or 11
- **Programming** : Python 3.8
- **Frameworks** : Flask

- **Database** : MySQL
- **Web Server** **:** WampServer
- **Web Design** **:** HTML, CSS, and Bootstrap

5.1. PYTHON

- Python is a high-level, object-oriented, interactive, general-purpose interpreted programming language. Guido van Rossum designed it between 1985 and 1990. The GNU General Public License (GPL) also applies to Python source code, just like it does to Perl. Enough knowledge about the Python programming language is provided by this tutorial.
- Python is an object-oriented, high-level, interpreted scripting language. Python was created with ease of reading in mind. It has fewer syntactical structures than other languages and frequently use English keywords, whereas other languages utilise punctuation. Students and working professionals who want to become excellent software engineers must learn Python, especially if they are in the web development field. At the moment, Python is the most popular high-level, multipurpose programming language. Python supports both procedural and object-oriented programming paradigms.

5.2. Pandas

Built on top of the Python programming language, pandas is an open source data analysis and manipulation tool that is quick, strong, adaptable, and simple to use. Working with "relational" or "labelled" data is made simple and intuitive with the help of the Python module pandas, which offers quick, adaptable, and expressive data structures. It seeks to serve as the core high-level building block for using Python to perform useful, real-world data analysis.

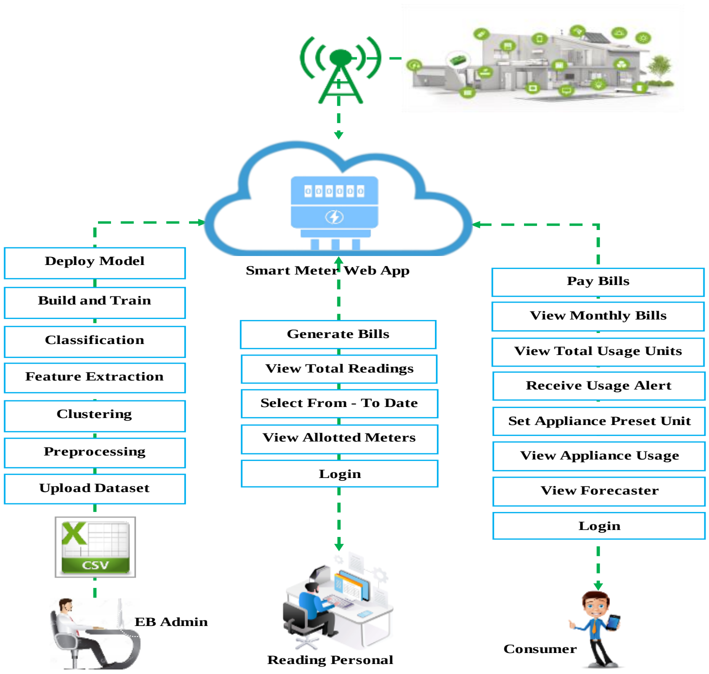
5.3. NumPy

The library known as NumPy, or Numerical Python, contains multidimensional array objects as well as a number of processing functions. NumPy can be used to conduct logical and mathematical operations on arrays.

5.4. MYSQL 5

The Structured Query Language, the most widely used language for organising and accessing database records, is the foundation of the relational database management system MySQL. MySQL is a free and open-source program that is licensed under the GNU. The company Oracle supports it. The MySQL database offers guidance on database administration and data manipulation through a variety of SQL queries. These queries include: build tables, drop tables, select records, update records, delete records, and insert records. To aid in your comprehension of the MySQL database, there are also provided MySQL interview questions.

6.1. SYSTEM ARCHITECTURE



7.1. SOFTWARE TESTING

Functional testing, performance testing, security testing, and usability testing are some of the methods that can be used to evaluate the software for the smart meter firmware project that uses LSTM to anticipate and monitor the consumption of domestic electrical appliances.

7.1.1. TESTING METHODOLOGY

Unit Testing: This type of testing makes sure that distinct system components, including functions and methods, are operating as intended. To evaluate

each module's functionality, including the web admin, consumer, reading personnel, notification, and reporting modules, we can create test cases.
Integration Testing: This type of testing makes sure that the system's many components are integrated and functioning as a whole. We can verify that the web admin, consumer, reading staff, notification, and reporting modules are all integrated and working properly by testing their communication.
System testing: This technique tests the system as a whole to make sure it satisfies the requirements and specifications. System testing aids in locating and resolving problems that emerge from the way the system's many components interact.

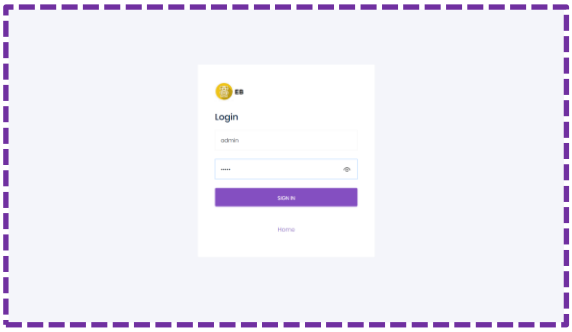
8.1. PROJECT DESCRIPTION

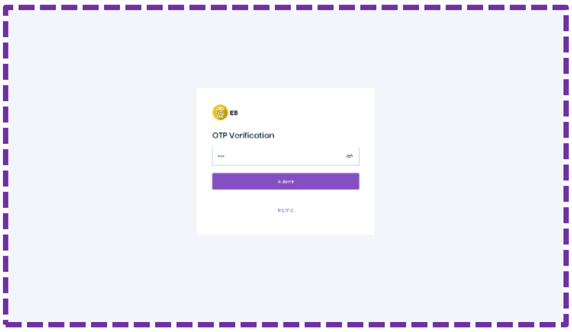
The project's goal is to create a system that will assist homes in tracking, managing, and predicting how much energy they consume. The technology, which consists of a web application and a machine learning algorithm, is made to function with smart meters that are put in homes. Three distinct interfaces will be included in the online application: one for the web administrator, one for users, and one for reading staff. The administrator can establish use limitations for each appliance and train the smart meter data via the online admin panel. Additionally, it offers an interface for processing payments and viewing generated bills. The Long Short-Term Memory (LSTM) machine learning technique, a kind of neural network that works well for time-series data forecasting, was employed in this study.
The reading staff can create readings and update the database with the help of the login. The usage of household electrical appliances is predicted and tracked by the forecasting and monitoring module using LSTM. Depending on the usage restriction that customers select, the system will also be able to regulate how much energy is used by household appliances. A microcontroller coupled to the home appliances will be used to accomplish this feature. MySQL and Python Flask will be used in the system's construction. The web application will be developed using the Flask framework, and smart meter data and other relevant information will be stored in a MySQL database.

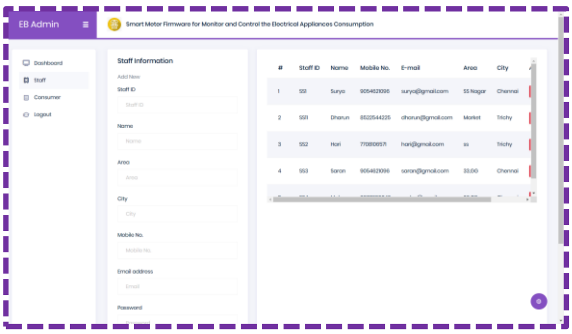
8.2. Reporting

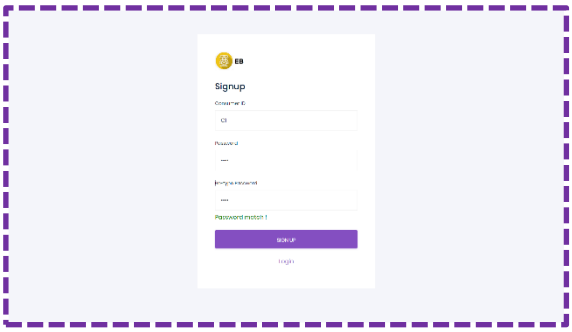
The reporting module is in charge of producing different reports using the information gathered by the firmware system of the smart meter. information of many kinds, including usage, billing, and energy consumption information, are available in this module. Details on how much energy each household appliance uses are included in the use report. The user can use this information to discover appliances that use a lot of energy and make the required changes to lower their usage. The billing report gives details about a household's energy usage and the bill that was produced for that specific billing cycle. cut back on energy use during those times. Data analysis and visualisation techniques are applied in the reporting module.

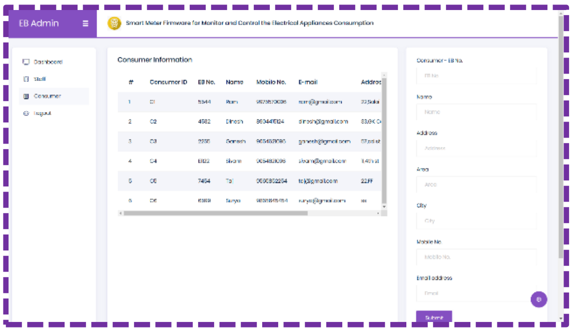
APPENDEX

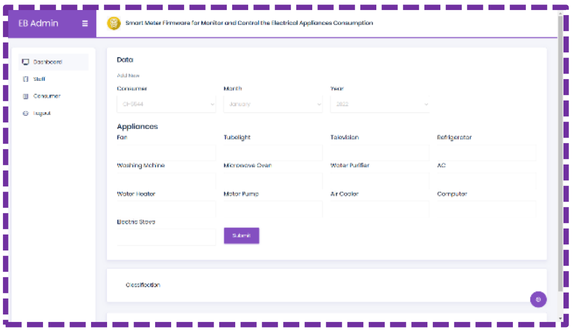


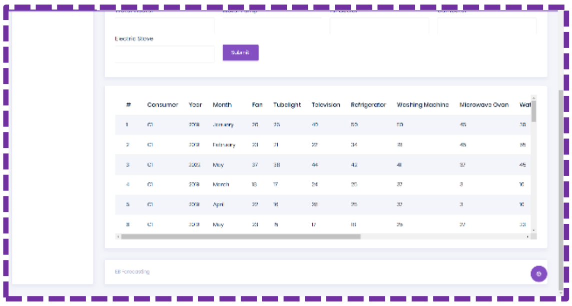


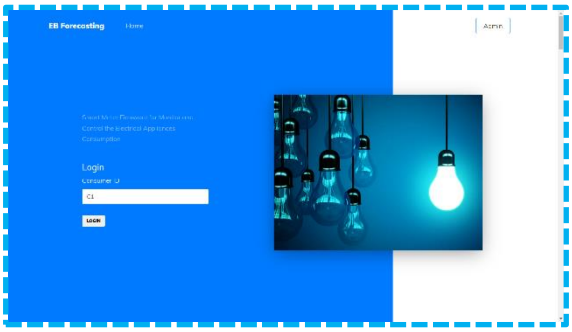












10.1. CONCLUSION

In conclusion, the project using LSTM for forecasting and monitoring and controlling household electrical appliances consumption and take online reading is an important and feasible project. It aims to provide consumers with the ability to monitor and manage their energy usage, set usage limits, view generated bills, and make payments online. The project's scope includes functionalities such as web administration for training smart meter data, consumer access to individual appliance consumption, setting usage limits, and generating bills. The LSTM algorithm is used for forecasting and monitoring household electrical appliance consumption, and Python Flask and MySQL are used for implementation. The project's feasibility study indicated that it is feasible, and the implementation process is manageable.

The project is significant because it has the potential to lower energy bills, raise consumer awareness of energy consumption, and support energy conservation initiatives. Black box and white box testing techniques, with an emphasis on unit testing, were used to test the project. The test findings demonstrated that the output design complied with project specifications and that the project's functioning aligned with its goals. To sum up, the smart meter firmware project could lower energy costs, raise customer awareness of energy use, and support energy conservation initiatives. The project is practical and provides the capability required to achieve its goals, as demonstrated by the implementation and testing process. An extra degree of intelligence is added when LSTM is used to forecast energy usage.

10.2. FUTURE ENHANCEMENT

There are countless chances for future improvements, and as technology develops, new ways to improve the firmware of smart meters for forecasting, monitoring, and managing the consumption of domestic electrical appliances will become available.

1. Integration with Renewable Energy Sources: Solar panels, wind turbines, and geothermal systems are examples of renewable energy sources that can be integrated into the system to improve it. It is possible to train the LSTM model to predict energy generation from renewable sources and, in turn, the energy consumption of certain appliances.
2. Advanced Analytics: To find patterns in energy consumption and spot anomalies in energy usage, the system can be improved by utilising advanced analytics techniques like clustering, regression, and anomaly detection. This can assist users in locating energy-saving opportunities.
3. Integration with Virtual Assistants: By incorporating virtual assistants such as Google Assistant or Alexa, the system can be improved. The system is

more user-friendly because users may use voice commands to operate specific appliances.

4. Energy Optimisation: By adding algorithms that optimise energy consumption for certain appliances according to their usage patterns, the system can be improved. Users may be able to lower their carbon footprint and energy costs as a result.

5. Integration with Smart Grid: By connecting with the smart grid, the system can be improved. Individual appliance energy consumption can be optimised by using the real-time energy pricing data that the smart grid can supply.

6. Predictive Maintenance: By employing predictive maintenance strategies to forecast when specific appliances are most likely to break, the system can be improved. This can assist users in planning maintenance tasks and preventing downtime.

7. Integration with Smart Cities: By integrating with smart cities, the system can be improved. This can give access to information on weather, traffic, and other variables that may have an impact on energy use. This information can be used to train the LSTM model, which will produce predictions of energy usage that are more accurate.

Integration with Smart Cities: The system can be enhanced by integrating with smart cities. This can provide access to data on traffic, weather, and other factors that can affect energy consumption. The LSTM model can be trained to incorporate this data and provide more accurate energy consumption forecasts.

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