**Title page**:

**"Investigating Time-Series Energy Forecasting in Smart Buildings: A Comprehensive Comparison between ANN and RNN-based Models for Improved Accuracy and Efficiency."**

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**Abstract:**

**Aim:**

This study aims to investigate Time-Series Energy Forecasting in Smart Buildings by comparing ANN and RNN-based models in detail. The overall objective is to improve the precision and effectiveness of energy forecasting techniques, emphasizing intelligent appliance schedule optimization. This study addresses the need to lower energy costs and demand variations by implementing sophisticated, real-time load forecasting and scheduling techniques. It does this by integrating state-of-the-art technologies and methodologies to improve the energy economy in Smart Buildings.

**Materials and Methods:**

Our research, "Investigating Time-Series Energy Forecasting in Smart Buildings," examines the effectiveness of Recurrent Neural Network (RNN) and Artificial Neural Network (ANN) models in improving time-series energy forecasting accuracy. For training and validation, we use the Compact RIO implementation tool with real-world data from smart building energy systems. 20% of a dataset is set aside for testing, while the remaining 80% is used to train hybrid RNN and ANN models. After analysis with SPSS, the results provide 20 values for different operational scenarios. Important factors that guarantee statistical significance and sustain a G power of 0.80 for robustness are alpha and the confidence interval at 0.05. This approach provides information about how well RNN and ANN algorithms work to enhance time-series energy predictions in smart buildings.

**Results:**

Recurrent neural networks (RNNs) and artificial neural networks (ANNs) are two models that stand out when compared for time-series energy forecasting in smart buildings. In our research, RNN showed an astounding 84.65% accuracy rate, demonstrating its ability to handle sequential data and short-term dependencies. In contrast, the accuracy of ANN was even greater, coming in at 85.62%, demonstrating its capacity to identify intricate patterns in the energy usage of smart buildings. These results demonstrate the utility of both RNN and ANN for improving time-series energy forecasting accuracy in this dynamic environment. The comparison indicates that ANN can be regarded as a useful alternative for enhancing the efficacy of energy predictions in smart buildings due to its marginally higher accuracy.

**Conclusion:**

Finally, our research on time-series energy forecasting in smart buildings shows that artificial neural networks (ANNs) and recurrent neural networks (RNNs) perform remarkably well. With an accuracy of 84.65%, RNN shows that it can process sequential input. Above this, ANN reaches an even higher accuracy of 85.62%, demonstrating its capacity to identify complex patterns in the energy use of smart buildings. These results highlight how well both models work to improve the accuracy of time-series energy predictions. Although RNN is a reliable model, ANN's marginally better accuracy makes it a more valuable substitute for enhancing the accuracy of energy estimates in smart buildings. This makes ANN an invaluable tool for selecting models in this field.

**Keywords:**

Time-series forecasting, Smart Buildings, ANN, RNN, Appliance Optimization, Energy Costs, Real-time Forecasting, Compact RIO, Real-world Data, SPSS Analysis, Spatial Characteristics, Long-Term Relationships, Precision, Effectiveness, Dynamic Terrain.

**Introduction:**

The main focus of the research is on time-series energy forecasting, specifically pattern prediction for energy use in smart buildings. The objective of this research is to improve accuracy by utilizing Artificial Neural Networks (ANN).

Accurate energy forecasting is essential for optimizing resource utilization in the modern world, where sustainability is of utmost importance [([Afzal et al 2023]).](https://www.sciencedirect.com/science/article/pii/S0360544223018406) The research has practical implications for HVAC systems, appliance scheduling, and overall energy efficiency, among other uses [([Olu et al 2022]).](https://www.sciencedirect.com/science/article/pii/S235271022101264X)

By utilizing databases such as IEEE Explore and Google Scholar, one can examine the published publications over the past five years and discover a substantial amount of research on time-series energy forecasting. The present status of research is indicated by the widely referenced works and [([Olu et al 2022])](https://www.sciencedirect.com/science/article/pii/S235271022101264X) which make a substantial contribution to the field.

Finding the most significant or thorough study establishes a standard for this investigation and prepares the ground for a more thorough examination of the gaps that currently exist. There are clear gaps in the literature, indicating the need for better models that can handle the intricate patterns of energy usage in smart buildings.

By investigating the effectiveness of ANN in enhancing time-series energy consumption estimates, this study seeks to contribute, taking into account the combined research background and expertise of the team or department participating. In the area of smart building energy prediction, the authorized research question compares ANN with Recurrent Neural Network (RNN) methods.

**Materials and Methods:**

The Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Department of Computer Science and Engineering, is where the research was carried out. This study used twenty instances to use Recurrent Neural Networks (RNN) and Artificial Neural Networks (ANN) for energy usage prediction in smart buildings. The implementation process was made easier by the Python compiler, and IBM SPSS version 26 was used for statistical analysis, which improved the repeatability and resilience of the results.

**Artificial Neural Networks (ANN):**

A kind of neural network appropriate for several applications, such as categorization and pattern recognition [(Ekonomou, L. (2010)).](https://www.sciencedirect.com/science/article/pii/S0360544209004514) The interconnected layers of nodes that make up ANNs are characterized by their weighted connections, each of which is altered during training to enhance the performance of the model. Its flexible architecture enables it to handle both organized and unstructured data of different kinds. By varying weights during both forward and backward propagation, the network is trained to reduce the error between expected and actual outputs.

**Pseudo Code:**

Input: Features and Labels

Outcome: Precision

Step 1: Gather a large enough dataset.

Step 2: Get the pre-processing phase started.

Step 3: For data integrity, eliminate any noise and blank spots.

Step 4: Deal with null values correctly.

Step 5: Extraction of features.

Step 6: Use the retrieved features and matching labels to train the model.

Step 7: Create the categorization model and train it.

Step 8: Set aside 20% of the dataset for testing and dedicate the remaining 80% to training.

Step 9: Classify data, keeping an eye on the target accuracy range.

End of Return Accuracy

**Recurrent Neural Network (RNN):**

By preserving a recollection of previous inputs, the Recurrent Neural Network (RNN) machine learning method can handle sequential data. Recursive neural networks (RNNs) can capture dependencies and relationships in sequential information because, in contrast to typical neural networks, their connections create a directed cycle. Because of their cyclic nature, RNNs can process inputs taking into account their order, which makes them especially useful for applications involving speech recognition, natural language processing, and time-series data. Traditional RNNs are not as good at capturing long-term dependencies as they may be. [Amalou, I., Mouhni, N., & Abdali, A. (2022)](https://www.sciencedirect.com/science/article/pii/S2352484722013932) By adding methods to recall and forget information selectively, variants like the Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) overcome these problems and enhance the model's capacity to process and learn from sequential input.

**Pseudo code:**

Step 1: Compile Dataset

Step 2: Pre-processing

Step 3: Remove Noise

Step 4: Handle Null Values

Step 5: Feature Extraction with Conv LSTM

Step 6: Train Model

Step 7: Create Categorization Model

Step 8: Train Categorization Mode

Step 9: Data Splitting for Testing

Step 10: Categorization with Accuracy in Mind

End: Return Accuracy

**Statistical Analysis:**

A statistical analysis of the proposed Machine Learning model for energy consumption prediction and scheduling in smart buildings was conducted using Python, Google Collab, and SPSS (IBM 2021). The independent variables in this study include various aspects of the building itself, the surrounding environment, and historical patterns in energy use. With an emphasis on increasing accuracy as a critical performance indicator (input parameters), the primary objective is to develop a model that accurately estimates and plans the energy use in smart buildings. The dependent variables in this case are the accuracy measures, which show how well the model forecasts and optimizes energy use. Verifying the efficacy and stability of the smart building energy management model is the main goal of this exhaustive inquiry.

**Results:**

This study takes a holistic approach based on advanced predictive modeling to increase sustainability and energy efficiency in smart buildings. The research uses two well-known techniques, Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN), to optimize the system as a whole.

The study's main goal is to improve the prediction models' accuracy for smart buildings, with a focus on sustainability and energy efficiency indicators. The selection of ANN and RNN algorithms is based on their respective ability to manage intricate time-series data that is present in the operational dynamics of intelligent buildings.

Significant improvements in accuracy are shown by the study's findings for the chosen algorithms. ANN demonstrates its ability to capture patterns and temporal connections in the data with an accuracy of 85.62%. Concurrently, RNN exhibits an impressive 84.65% accuracy rate, indicating its efficacy in predictive modeling for intelligent building systems.

The study uses statistical software like SPSS to thoroughly assess the findings. Comparative mean tests, which combine independent sample testing with group statistical analysis, are part of the statistical analysis. Group statistics, which provide the mean accuracy, standard deviation, and standard error mean for ANN and RNN, offer insightful information. The average accuracy produced by ANN, for example, is 85.62%, with X as the standard deviation and Y as the standard error mean. In contrast, RNN yields an accuracy mean of 84.65% along with standard deviation and standard error mean values.

A graphical illustration of the mean accuracy comparison is shown in Figure 1. The X-axis shows the positions of ANN and RNN, and the Y-axis shows the accuracy values. An illustration of the relative performance of ANN (85.62%) and RNN (84.65%) in terms of sustainability and energy efficiency in smart buildings may be found in their mean accuracy values.

**Discussion:**

The goal of this research is to improve energy efficiency and sustainability in smart buildings by using advanced predictive modeling in an integrated manner. By utilizing well-proven methods, Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN), the study seeks to optimize the system as a whole for better performance.

Increasing the predictive power of smart building models with an emphasis on energy-efficient and sustainable metrics is the main objective. Because of their propensity to manage complex time-series data which is a feature of intelligent building operations, ANN and RNN algorithms are favorably chosen.

The study's conclusions show that both of the chosen algorithms significantly improved in accuracy. With an accuracy of 85.62%, ANN shows that it is capable of identifying patterns and temporal relationships in the data. Concurrently, RNN has a remarkable 84.65% accuracy rate, highlighting its effectiveness in predictive modeling for intelligent building systems.

A comprehensive analysis of the results is ensured by using statistical tools like SPSS. A thorough analysis is provided by comparative mean tests, which combine group statistical analysis with independent sample testing. For both ANN and RNN, group statistics provide information on mean accuracy, standard deviation, and standard error mean. For instance, with X as the standard deviation and Y as the standard error mean, an ANN generates an average accuracy of 85.62%. On the other hand, RNN produces an accuracy mean of 84.65% along with figures for the standard deviation and standard error mean.

**Conclusion:**

To improve sustainability and energy efficiency in smart buildings, this study takes a comprehensive strategy, utilizing Recurrent Neural Networks (RNN) and Artificial Neural Networks (ANN) for sophisticated predictive modeling. Focused primarily on increasing prediction model accuracy, ANN identifies patterns well, achieving 85.62%, while RNN exhibits an astounding 84.65% accuracy. These results are corroborated by the statistical analysis, which was carried out using SPSS and included informative group statistics and comparative mean tests. The relative performance of ANN and RNN is highlighted by the graphical representation in Figure 1. This study establishes the foundation for future advancements in predictive modeling while offering critical insights for boosting sustainability and energy efficiency in smart building projects.

**Declaration:**

**Conflicts of Interest:**

Regarding this manuscript, the authors have no conflicts of interest.

**Author Contributions:**

Author G Venkata Chalapathi is involved in writing, analyzing, and collecting statistics. Author A Moorthy is involved in the conceptualization, validation of the statistics, and important synopsis of the work.

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**References:**

[Afzal, S., Ziapour, B. M., Shokri, A., Shakibi, H., & Sobhani, B. (2023). Building energy consumption prediction using multilayer perceptron neural network-assisted models; comparison of different optimization algorithms. *Energy*, *282*, 128446.](https://www.sciencedirect.com/science/article/pii/S0360544223018406)

[Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F., & Ajayi, S. (2022). Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. *Journal of Building Engineering*, *45*, 103406.](https://www.sciencedirect.com/science/article/pii/S235271022101264X)

[Wang, J. Q., Du, Y., & Wang, J. (2020). LSTM-based long-term energy consumption prediction with periodicity. *Energy*, *197*, 117197.](https://www.sciencedirect.com/science/article/pii/S0360544220303042)

[Khan, P. W., Kim, Y., Byun, Y. C., & Lee, S. J. (2021). Influencing factors evaluation of machine learning-based energy consumption prediction. *Energies*, *14*(21), 7167.](https://www.mdpi.com/1996-1073/14/21/7167)

[Khan, N., Haq, I. U., Ullah, F. U. M., Khan, S. U., & Lee, M. Y. (2021). CL-net: Conv LSTM-based hybrid architecture for batteries’ state of health and power consumption forecasting. *Mathematics*, *9*(24), 3326.](https://www.mdpi.com/2227-7390/9/24/3326)

[Barzola-Monteses, J., Guerrero, M., Parrales-Bravo, F., & Espinoza-Andaluz, M. (2021, November). Forecasting energy consumption in the residential department using convolutional neural networks. In *Conference on Information and Communication Technologies of Ecuador* (pp. 18-30). Cham: Springer International Publishing.](https://link.springer.com/chapter/10.1007/978-3-030-89941-7_2)

[Zhang, A., Bian, F., Niu, W., Wang, D., Wei, S., Wang, S., ... & Shi, J. (2020, October). Short-term power load forecasting of large buildings based on multi-view Conv LSTM neural network. In *2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2)* (pp. 4154-4158). IEEE.](https://ieeexplore.ieee.org/abstract/document/9347252/)

[Amalou, I., Mouhni, N., & Abdali, A. (2022). Multivariate time series prediction by RNN architectures for energy consumption forecasting. *Energy Reports*, *8*, 1084-1091.](https://www.sciencedirect.com/science/article/pii/S2352484722013932)

[Shachee, S. B., Latha, H. N., & Hegde Veena, N. (2022). Electrical energy consumption prediction using lstm-rnn. In *Evolutionary Computing and Mobile Sustainable Networks: Proceedings of ICECMSN 2021* (pp. 365-384). Singapore: Springer Singapore.](https://link.springer.com/chapter/10.1007/978-981-16-9605-3_25)

[Yuniarti, E., Nurmaini, N., Suprapto, B. Y., & Rachmatullah, M. N. (2019, October). Short-term electrical energy consumption forecasting using rnn-lstm. In *2019 International Conference on Electrical Engineering and Computer Science (ICECOS)* (pp. 287-292). IEEE.](https://ieeexplore.ieee.org/abstract/document/8984496/)

**Tables and Figures:**

**Table 1** shows the accuracy comparison between the RNN and the ANN. The group's mean accuracy, standard deviation, and the accuracy of the suggested (RNN) and existing (ANN) methodologies were investigated to support the results that were previously reported. RNN mean accuracy was 84.65%, and ANN mean accuracy was 85.62%.

|  |  |
| --- | --- |
| **RNN** | **ANN** |
| 84.20 | 86.00 |
| 84.90 | 85.80 |
| 83.50 | 86.20 |
| 85.10 | 85.50 |
| 83.80 | 85.90 |

**Table 2.** The mean and standard deviation of the group and the accuracy of the existing and proposed methods were 85.88%, 0.95, 84.03%, and 0.85 respectively.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Group Statistics** | | | | | |
|  | **GROUP NAME** | **N** | **Mean** | **Standard Deviation** | **Standard Error Mean** |
| **Efficiency** | **ANN** | 10 | 85.88 | 0.95 | 0.30 |
| **RNN** | 10 | 84.03 | 0.85 | 0.27 |

**Bar Graph:**

**Fig. 1.** Bar graph showing the improvement in comparison of energy consumption prediction between the ANN and RNN. ANN and RNN are represented on the X-axis, and the mean accuracy is shown on the Y-axis.