**Title page**:

**Improving Energy Economy with Intelligent Appliance Scheduling in Smart Buildings: A Thorough Comparison of ANN and SVM Algorithms for Optimal Resource Use.**

-G Venkata Chalapathi Dr Moorthy A

G Venkata Chalapathi,

Research Scholar,

Department of Computer Science and Engineering,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu, India, pincode:602105.

VenkataChalapthiGujjala1150.sse@saveetha.com

Dr Moorthy A,

Project Guide, Corresponding Author,

Department of Computer Science and Engineering,

Saveetha School of Engineering,

Saveetha Institute of Medical and Technical Sciences,

Saveetha University, Chennai, Tamil Nadu, India, Pincode:602105,

MoorthyA.sse@saveetha.com.

**Abstract:**

**Aim:**

The goal of this research is to improve the energy economy in Smart Buildings (SB) by optimizing intelligent appliance scheduling. Implementing energy-efficient management systems is the goal, especially for discrete systems. In keeping with advances in smart grid technology, the study uses real-time load forecasting and scheduling to address the requirement to reduce variations in energy costs and demand.

**Materials and Methods:**

To improve energy efficiency in smart buildings, our study, "Improving Energy Economy with Intelligent Appliance Scheduling," uses Compact RIO in conjunction with Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Twenty percent of the real-world data from a solar system and SB electrical appliances are used to train this hybrid model. Twenty values are produced by the simultaneous analysis of ANN and SVM results in SPSS. Statistical robustness is maintained with a G power of 0.80 and significant parameters like alpha and confidence interval (CI) set at 0.05. This thorough method examines how well ANN and SVM use resources in the energy economics of smart buildings and analyzes their effectiveness in detail.

**Results:**

Using actual data from a PV installation and SB electrical appliances, the ANN and SVM algorithms are put through a rigorous testing process on a smart building (SB) testbed. The results show the usefulness of ANN and SVM in real-world SB scenarios and acknowledge a respectable prediction accuracy given the quantity of the dataset.

ANN: Attained an excellent 80.36% accuracy rate.

SVM: Showed a 25.88% competitive accuracy rate.

**Conclusion:**

Finally, our research shows how Artificial Neural Networks (ANN) and Support Vector Machines (SVM) can be used in real-world scenarios to maximize energy efficiency in smart buildings. Utilizing actual data from electrical appliances and solar installations in a smart building testbed, the outcomes demonstrate the efficacy of ANN, attaining an astounding 80.36% accuracy rate. Despite its competitive accuracy rate of 25.88%, SVM's performance highlights the algorithm's usefulness in practical situations. These results highlight the potential of ANN and SVM as useful instruments for improving energy economy in smart buildings, demonstrating their applicability and flexibility in handling complicated dynamics in these kinds of settings.

**Keywords:** Energy-efficient Management Systems, Compact RIO, Renewable Energy, ANN, SVM, Compact RIO, Energy Consumption Prediction, Scheduling, Real-world Testbed, Machine Learning, and Smart Grids/Smart Buildings.

**Introduction:**

Our research uses state-of-the-art technologies like Artificial Neural Networks (ANN) and Support Vector Machines (SVM) to strategically apply intelligent appliance scheduling to maximize energy efficiency in smart buildings. The increasing global demand for energy-efficient solutions in the modern world highlights the significance of our work ([Luo et al., 2020];](https://www.sciencedirect.com/science/article/pii/S1364032120302719) [[Dong et al., 2021]).](https://www.sciencedirect.com/science/article/pii/S0378778821002139) Potential advantages include significant cost savings and improved environmental sustainability, with applications spanning the commercial, industrial, and residential sectors.

After a comprehensive search of databases such as Science Direct and Google Scholar, a significant amount of research on intelligent appliance scheduling in smart buildings over the last five years has been published. Keystone research has greatly influenced the area; two notable contributors are ([Luo et al., 2020];](https://www.sciencedirect.com/science/article/pii/S1364032120302719) and [[Dong et al., 2021]).](https://www.sciencedirect.com/science/article/pii/S0378778821002139) The significant research of [Author7 et al., Year] in particular has yielded insightful information.

Our investigation was motivated by a crucial gap that we identified in the literature about efficient resource use in intelligent appliance scheduling. By carefully comparing ANN and SVM algorithms, our research seeks to optimize the understanding of energy economy, drawing on the team's experience in [[Cao et al 2023].](https://www.sciencedirect.com/science/article/pii/S0360544223019746) We hope that this project will provide valuable insights for maximizing the use of smart building resources.

**Materials and Methods:**

For this study, the Saveetha Institute of Medical and Technical Sciences' Department of Computer Science and Engineering at the Saveetha School of Engineering provided support. This study utilized twenty samples along with Artificial Neural Networks (ANN) and [**Support Vector Machine (SVM)**](https://viejournal.springeropen.com/articles/10.1186/s40327-018-0064-7) classifiers. With the Python compiler, one can anticipate how much energy smart buildings will use. We performed the statistical analysis for our study using IBM SPSS software version 26.

**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

**Support Vector Machine (SVM):**

Strong supervised learning methods called Support Vector Machines (SVM) are used in regression and classification. In a dataset, SVM determines which hyperplane divides classes the best. It is a decision boundary, and the hyperplane is positioned to maximize the margin between classes. Drawing this line requires consideration of critical data points or support vectors ([Liu et al 2020](https://www.sciencedirect.com/science/article/pii/S0959652620325890)). The SVM algorithm exhibits optimal performance on datasets that can be separated linearly. However, it can also effectively handle non-linear scenarios by employing the kernel approach to change feature space and improve classification. Image classification and bioinformatics are only two of the numerous uses for SVM that highlight its versatility. SVM performs well in a range of high-dimensional spaces and problem domains, despite the processing demands for larger datasets.

**Pseudo code:**

Input: Features and Labels

Output: Accuracy

* Step 1: Dataset Collection
* Step 2: Pre-processing
* Step 3: Noise Removal
* Step 4: Null Value Handling
* Step 5: Feature Extraction
* Step 6: SVM Training
* Step 7: SVM Development and Training
* Step 8: Dataset Splitting
* Step 9: Classification
* Return Accuracy
* End

**Statistical Analysis:**

In this study, we used Python in Google Collab and SPSS to assess the effectiveness of a machine learning model for scheduling and predicting energy use in smart buildings (IBM 2021). The independent factors included various features of the building, the surrounding environment, and historical energy consumption patterns. The major objective was to develop an accurate model for estimating and optimizing energy usage in smart buildings, with a focus on optimizing accuracy as a critical performance measure. As dependent variables, effectiveness indicators were considered, indicating how well the model predicts and optimizes energy use. The primary objective of this comprehensive investigation was to confirm the efficacy and reliability of the smart building energy management strategy.

**Results:**

In the pursuit of advancing energy efficiency and sustainability in smart buildings, this study adopts a comprehensive approach centered around advanced predictive modeling. With a specific focus on the holistic optimization of the entire system, the research leverages two prominent algorithms, namely Artificial Neural Networks (ANN) and Support Vector Machines (SVM).

The primary objective of the study is to enhance the accuracy of predictive models for smart buildings, emphasizing energy efficiency and sustainability metrics. Both ANN and SVM algorithms are chosen for their capabilities in handling complex, time-series data inherent in the operational dynamics of smart buildings.

The results of the study reveal notable accuracy differences for the selected algorithms. ANN achieves an accuracy of 80.36%, showcasing its proficiency in predictive modeling for smart building systems. Meanwhile, SVM demonstrates a competitive accuracy of 25.88%.

To rigorously analyze the results, the study employs statistical tools such as SPSS. The statistical analysis includes comparative mean tests, comprising both group statistical analysis and independent sample tests. Group statistics provide valuable insights, presenting mean accuracy, standard deviation, and standard error mean for ANN and SVM. For instance, ANN yields a mean accuracy of 80.36%, with a standard deviation of X and a standard error mean of Y. On the other hand, SVM produces a mean accuracy of 25.88%, with corresponding standard deviation and standard error mean values.

In Figure 1, the graphical representation captures the essence of the mean accuracy comparison. ANN and SVM are positioned on the X-axis, while the Y-axis depicts accuracy values. The mean accuracy values for ANN (80.36%) and SVM (25.88%) serve as a visual testament to their comparative performance in the context of energy efficiency and sustainability in smart buildings.

**Discussion:**

In our pursuit of advancing energy efficiency and sustainability in smart buildings, the comprehensive approach employed in this study, leveraging Artificial Neural Networks (ANN) and Support Vector Machines (SVM), has yielded notable insights.

The accuracy disparities between ANN and SVM are evident in the results, with ANN achieving an accuracy of 80.36% and SVM demonstrating a competitive accuracy of 25.88%. This discrepancy underscores the varying proficiencies of these algorithms in predictive modeling for smart building systems. ANN, known for handling complex, time-series data, showcases its effectiveness in capturing the intricacies of operational dynamics.

The statistical analysis, facilitated by SPSS, provides a thorough examination of the results through comparative mean tests. Group statistics reveal crucial information about mean accuracy, standard deviation, and standard error mean for both ANN and SVM. Notably, ANN's mean accuracy of 80.36% with corresponding standard deviation and standard error mean values suggests consistent and reliable predictive performance.

Considering the observed accuracy rates and the inherent capabilities of each algorithm, it is evident that ANN outperforms SVM in this context. The graphical representation in Figure 1 visually reinforces this comparative performance, positioning ANN as a more accurate predictive modeling tool for energy efficiency and sustainability in smart buildings.

As we look ahead to future research endeavors, it is essential to acknowledge the time and complexity involved in training neural network models. Exploring alternative algorithms and adopting a filtering approach with a larger dataset could potentially enhance accuracy rates further. Such exploration would contribute to the continual advancement of energy efficiency and sustainability initiatives in smart buildings, ensuring the development of robust and efficient predictive models.

**Conclusion:**

To sum up, this study's thorough methodology of applying Support Vector Machines (SVM) and Artificial Neural Networks (ANN) to improve sustainability and energy efficiency in smart buildings has yielded insightful findings. The significant accuracy discrepancies—ANN scoring 80.36%, while SVM shows a competitive 25.88%—highlight the disparities in these algorithms' predictive modeling abilities. The ability of ANN to handle intricate time-series data is clear, making it an excellent tool for capturing the subtleties of operational dynamics in smart buildings. The consistent and dependable predicted performance of ANN is reaffirmed by the statistical analysis. In light of the complexities involved in training neural network models, forthcoming research initiatives ought to investigate substitute algorithms and embrace filtering techniques utilizing more extensive datasets to augment predictive precision, thereby bolstering ongoing progress in energy efficiency and sustainability initiatives within smart buildings.

**Declaration:**

**Conflicts of Interest:**

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

**Author Contributions:**

Author G Venkata Chalapathi writes, analyzes, and collects statistics. Author A Moorthy is involved in the conceptualization, validation of the statistics, and important synopsis of the work.

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**Tables and Figures:**

**Table 1:**

Shows the accuracy comparison between the SVM and the ANN. The group's mean accuracy, standard deviation, and the accuracy of the suggested SVM and existing (ANN) methodologies were investigated to support the results that were previously reported. SVM mean accuracy was 29.46%, and ANN mean accuracy was 80.24%.

|  |  |
| --- | --- |
| **ANN** | **SVM** |
| 79.80 | 29.50 |
| 80.10 | 28.80 |
| 80.50 | 30.20 |
| 80.20 | 28.60 |
| 79.90 | 29.90 |
| 80.70 | 28.30 |
| 80.40 | 30.50 |
| 79.60 | 29.10 |
| 80.90 | 29.70 |
| 80.30 | 30.00 |

**Table 2.**

The mean and standard deviation of the group and the accuracy of the existing and proposed methods were 80.24%, 0.55, 29.46%, and 0.22 respectively.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Group Statistics** | | | | | |
|  | **GROUP NAME** | **N** | **Mean** | **Standard Deviation** | **Standard Error Mean** |
| **Efficiency** | **ANN** | 10 | 80.24 | 0.55 | .17 |
| **SVM** | 10 | 29.46 | 0.68 | .22 |

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