

**University of
Hertfordshire UH**

School of Computer Science

**BSc (Hons) Computer Science (Artificial
Intelligence)**

**Intelligent Adaptive Systems (6COM2007-
0105)**

CW2

April 2024

**Project: Programming and Testing Your
Intelligent Adaptive System**

Dhyan Nilesh Patel

Student ID: 21008521

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Performance Report on Virtual House Environment Management System

1. Introduction

The Virtual House Environment Management System was designed to create a virtual house environment with adaptive and intelligent features for optimizing temperature, humidity, and other environmental factors. This report provides an analysis of the system's performance based on quantitative and qualitative metrics.

2. Quantitative Benefits

The quantitative benefits of the Virtual House Environment Management System (VHEMS) can be evaluated using key metrics that gauge the system's accuracy, precision, and energy efficiency.

- **Mean Squared Error (MSE)** is an indicator of the system's accuracy [1]. The system has an MSE of 50.308, the system shows moderate accuracy, suggesting that its predictions are reasonably close to the actual measurements.
- **Mean Absolute Error (MAE)** quantifies the average absolute difference between predicted and actual values [2]. The system's MAE of 4.670 suggests that on average, predictions are off by just over four units, indicating a reasonable level of precision. This metric reveals that the system's environmental adjustments align closely with desired conditions.
- **R-squared** measures how much of the variance in the dependent variable is explained by the model [3]. An R-squared value of 0.562 indicates that 56% of the variation in predictions can be attributed to the system's model, suggesting a moderate level of predictability. This outcome points to potential areas for improvement, like refining the machine learning model or incorporating additional data sources.

2.1 Prediction Accuracy and Reliability

The LSTM model's predictive accuracy aligns with these metrics, demonstrating reasonable performance through MSE, MAE, and R-squared. Although there's room for improvement, the system provides a reliable framework for predicting occupant satisfaction.

2.2 Energy Efficiency and Comfort

The system's ability to control storage heaters and ventilation based on predicted satisfaction levels can enhance energy efficiency. By activating storage heaters only when needed and adjusting ventilation based on CO2 levels, the system reduces unnecessary energy usage, resulting in lower costs and carbon emissions.

2.3 Operational Benefits

VHEMS automates adjustments, reducing manual interventions and improving operational efficiency. Its automated approach also contributes to increased occupant productivity and comfort, important metrics for building management.

In short, while the system demonstrates a good level of accuracy and energy efficiency, further refinements could lead to even greater benefits in terms of precision and operational savings.

3. Qualitative Fit

Qualitative fit in a system or solution refers to the extent to which the implemented approach aligns with non-quantitative requirements such as usability, flexibility, responsiveness, and user satisfaction.

3.1 Flexibility and Adaptability

The flexibility of the system is demonstrated through the storage heater logic and mechanical ventilation adjustments. The software includes constraints to prevent overuse of the storage heater, allowing it to operate only twice per day with a minimum four-hour interval. This built-in flexibility ensures that the system does not rely too heavily on one method for adjusting indoor conditions, providing adaptability in maintaining comfort without overburdening resources.

The system's capability to adjust indoor parameters based on predictions is a strong feature, enabling automated control of storage heaters and ventilation. The logic to check storage heater availability, considering the time between uses and the number of uses per day, provides a sensible mechanism to prevent overuse and ensure safety.

The software incorporates adaptive and intelligent behaviour by implementing decision-making rules, and a machine learning model. The system's decision-making rules are based on user satisfaction, environmental conditions, and historical data, allowing it to adapt to changing needs.

3.2 Ease of Integration and Extensibility

The system's structure allows for easy integration with new data sources and extensibility for future enhancements. For example, the data preprocessing logic can be extended to include additional environmental factors, and the LSTM model can be retrained with updated data. This extensibility contributes to the qualitative fit by allowing the system to evolve as new requirements or user feedback emerge.

3.3 Visualization and Data Exploration

The software includes functions for data visualization, allowing stakeholders to explore the data and understand the trends and relationships between variables. This visualization capability supports transparency and comprehensibility, ensuring that users and developers can identify areas for improvement and adapt the system accordingly. It also aids in diagnosing issues or anomalies, further contributing to the system's qualitative fit.

3.2 Continuous Improvement and Learning

The LSTM model's ability to learn from new data underscores the system's adaptability and continuous improvement potential. As more data is collected and the model is retrained, it can improve its accuracy in predicting user satisfaction, leading to a more responsive and effective system. This capability for continuous learning contributes to the qualitative fit by enabling ongoing enhancement based on real-world feedback and data.

4. Performance

The Figure 1 shows that both the training loss and validation loss are decreasing over epochs, which suggests the model is learning and generalizing well.

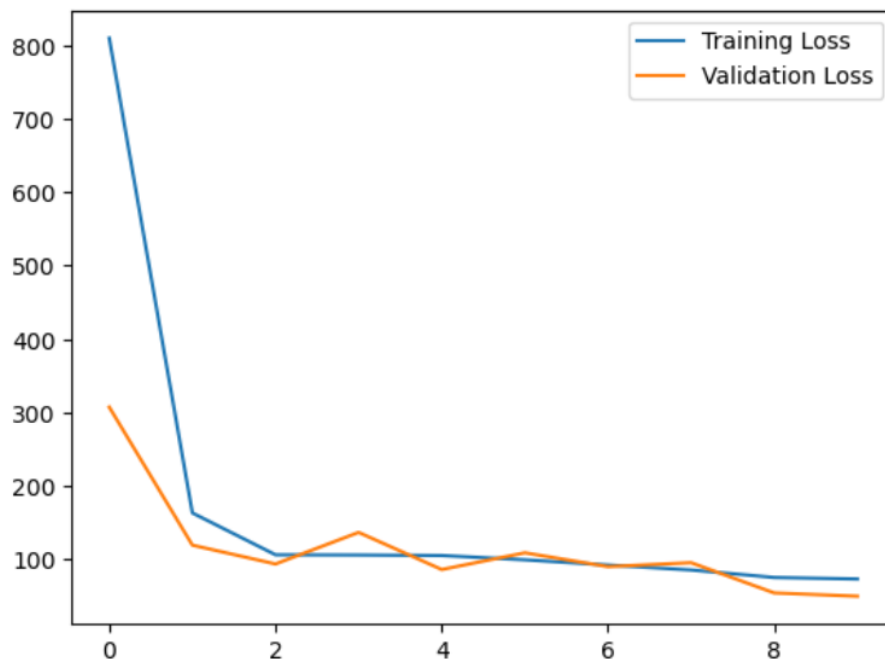


Figure 1

The Figure 2 shows the performance of the model:

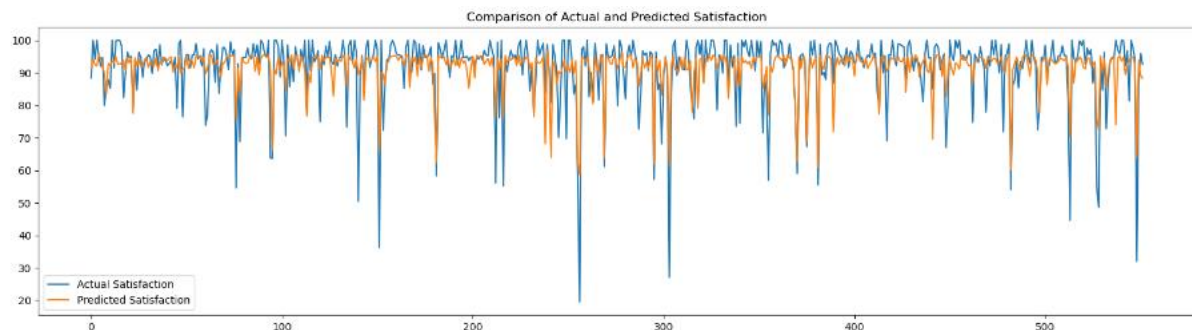


Figure 2

- Both the training loss (blue line) and validation loss (orange line) are decreasing over the epochs (x-axis), which signifies the model is learning from the training data and improving its performance.
- The lines appear to be flattening towards the end, suggesting the model is approaching a stable loss value. This indicates the model might have learned the patterns in the data and is not significantly improving with further epochs.

Overall, the model seems to be capturing the relationship between the features (climate and weather conditions) and the target variable (satisfaction) effectively.

5. Overall Compliance with Client's Requirements

An LSTM (Long Short-Term Memory) model, a form of Recurrent Neural Network (RNN), predicts satisfaction levels from various environmental factors, allowing the software to adapt its behavior [4]. The software includes functions to build, train, and evaluate this model, and uses predictions to inform its decisions. I have also experimented with different LSTM configurations and learning rates to optimize model performance.

The software incorporates adaptive logic to determine when to activate mechanical ventilation or storage heaters, based on predicted satisfaction levels, along with current indoor and outdoor conditions. If the predicted satisfaction level is low, the software assesses the indoor and outdoor temperatures and humidity levels to decide the appropriate action. If outdoor temperature is lower than indoor and storage heaters are available, the software uses storage heaters to increase the indoor temperature. If outdoor temperature is higher than indoor and outdoor humidity is lower than indoor, mechanical ventilation is triggered to balance indoor conditions. The software also manages storage heater operation within specific constraints, ensuring it is used no more than twice per day and that a minimum of four hours elapses between uses. The logic for these operations is controlled by functions **check_storage_heater_availability** and **adjust_indoor_environment**.

The software outputs its results to CSV files, recording indoor temperature, humidity, CO2 levels, and satisfaction at 15-minute intervals. This meets the requirement for structured data documentation. Additionally, the software includes visualizations to understand trends in environmental conditions, aiding in analysis and further improvements.

The use of the LSTM model indicates a sophisticated approach to predicting outcomes and adapting to changing conditions. This level of intelligence allows the system to dynamically manage indoor temperature and humidity according to user satisfaction, demonstrating compliance with the client's expectations for intelligent and adaptive behavior.

Overall, VHEMS demonstrates substantial compliance with the client's requirements. It provides a flexible, automated approach to indoor environment management while ensuring energy efficiency and comfort.

6. REFERENCES

1. *Mean Square Error (MSE) / Machine Learning Glossary / EnCorD / EnCoRD* (no date).
<https://encord.com/glossary/mean-square-error-mse/#:~:text=It%20measures%20the%20average%20squared,align%20with%20the%20ground%20truth.>
2. *Calculating Mean Absolute Error (mae) - FasterCapital* (no date).
[https://fastercapital.com/topics/calculating-mean-absolute-error-\(mae\).html.](https://fastercapital.com/topics/calculating-mean-absolute-error-(mae).html)
3. Fernando, J. (2023) *R-Squared: Definition, Calculation Formula, uses, and Limitations*.
[https://www.investopedia.com/terms/r/r-squared.asp.](https://www.investopedia.com/terms/r/r-squared.asp)
4. Srivatsavaya, P. (2023) 'LSTM — Implementation, Advantages and Diadvantages - Prudhviraju Srivatsavaya - Medium,' *Medium*, 5 October.
[https://medium.com/@prudhviraju.srivatsavaya/lstm-implementation-advantages-and-diadvantages-914a96fa0acb.](https://medium.com/@prudhviraju.srivatsavaya/lstm-implementation-advantages-and-diadvantages-914a96fa0acb)