Thesis Proposal

Title Page

Title: Smart Load Forecasting Model for Rural Electrical Grids in Bangladesh Using Machine Learning
Department: Computer Science and Engineering (CSE)
Institution: Jashore University of Science and Technology
Submitted By: Rakesh Biswas
Student ID: 200112
Supervisor: Monishanker Halder (Assisstant Professor)
Date:

---

1. Motivation, Existing Systems & Research Gaps

1.1 Motivation

In Bangladesh, rural electrification has made substantial progress through the Rural Electrification Board (REB) and Palli Bidyut Samities (PBS). However, rural areas continue to suffer from inefficient power distribution, frequent load shedding, and unreliable demand forecasting. With the growing population and the push for digital Bangladesh, ensuring stable electricity in rural regions is critical. Smart load forecasting can help optimize power distribution and reduce load mismatch.

1.2 Existing Systems

Current national-level forecasting in Bangladesh is largely statistical and aggregated. Tools used by BPDB and PBS rely on traditional load forecasting without advanced machine learning or AI-driven insights. Internationally, advanced countries use real-time smart meter data and AI models, but these are not yet adapted to Bangladesh's rural setup.

1.3 Research Gaps

- Lack of rural-focused load forecasting models using ML.
- Absence of localized datasets adapted to Bangladesh's electricity usage patterns.
- Little to no implementation of predictive analysis models tailored for low-infrastructure rural zones.

---

2. Objectives

- To design a machine learning-based model for forecasting electricity load in rural Bangladeshi areas.
- To validate predictions using publicly available and synthetic datasets.
- To compare model performances (Linear Regression, Decision Trees, XGBoost, LSTM, etc.).
- To visualize predicted data and make insights usable via a dashboard (optional).

---

3. Technology / Tools / Models / Architecture

Tools & Frameworks:

- Python, Jupyter Notebook, Google Colab
- Libraries: Pandas, NumPy, Scikit-learn, XGBoost, Matplotlib, Seaborn
- Optional Deep Learning: TensorFlow/Keras for LSTM models
- Streamlit or Flask (for optional dashboard)

Models:

- Linear Regression
- Decision Tree Regressor
- Random Forest Regressor
- XGBoost Regressor
- LSTM (optional advanced phase)

Architecture Overview:

- Data Collection → Preprocessing → Feature Engineering → Model Training → Evaluation → Visualization

---

4. Planning / Schedule (1 Year)

Phase	Duration	Tasks
Literature Review	Month 1-2	Study papers, identify methods and gaps
Dataset Preparation	Month 3-4	Data scraping, simulation, cleaning, and preprocessing
Model Development	Month 5-6	Baseline models (LR, RF), training, and evaluation
Advanced Models	Month 7	Implement XGBoost, optional LSTM for sequence prediction
Visualization	Month 8	Build dashboard (Streamlit/Flask)
Report Drafting	Month 9-10	Write thesis, include results, diagrams, and comparisons
Revision & Feedback	Month 11	Supervisor review and improvements
Final Submission	Month 12	Final formatting, printing, and submission

---

5. References (Q1/Q2 Journals)

1. Suganthi, L., & Samuel, A. A. (2012). *Energy models for demand forecasting—A review*. Renewable and Sustainable Energy Reviews, Elsevier. https://doi.org/10.1016/j.rser.2011.10.014

2. Li, K., Su, H., & Chu, J. (2011). *Forecasting building energy consumption using neural networks and hybrid neuro-fuzzy systems: A comparative study*. Energy and Buildings, Elsevier. https://doi.org/10.1016/j.enbuild.2011.06.034

3. Khan, M. J., Iqbal, M. T., & Mahbub, A. (2018). *Electric load forecasting using machine learning in smart grid: A case study from Bangladesh*. IEEE International Conference on Power, Energy and Control.

4. Taylor, J. W., & McSharry, P. E. (2007). *Short-term load forecasting methods: An evaluation based on European data*. IEEE Transactions on Power Systems.

5. Deb, C., Zhang, F., Yang, J., Lee, S. E., & Shah, K. W. (2017). *A review on time series forecasting techniques for building energy consumption*. Renewable and Sustainable Energy Reviews, Elsevier. https://doi.org/10.1016/j.rser.2017.01.085

[Specified : **1. Multivariate Machine Learning Algorithms for Energy Demand Forecasting in Bangladesh**

- **Authors**: [Authors not specified]
- **Published in**: *Energy Reports* (Elsevier), 2025
- **Link**: ScienceDirect Article
- **Summary**: This study presents deep learning frameworks for predicting electricity demand in the Western region of Bangladesh, utilizing Artificial Neural Networks (ANN). It emphasizes the importance of multivariate inputs for accurate forecasting.ScienceDirect
- **Research Gaps**:
    - Limited focus on rural grid-specific challenges.
    - Need for models that can handle data scarcity in rural areas.
- **Suggested Improvements**:
    - Incorporate hybrid models combining statistical and machine learning approaches.
    - Develop techniques to handle missing or sparse data common in rural settings.

---

2. Deep Learning Modeling in Electricity Load Forecasting

- **Authors**: [Authors not specified]
- **Published in**: *Energy Reports* (Elsevier), 2024
- **Link**: ScienceDirect Article

- **Summary**: This study explores the use of four machine learning-based methods for forecasting short to long-term electricity load. It highlights the effectiveness of deep learning models in capturing complex patterns in energy consumption data.ScienceDirect
- **Research Gaps**:
    - Lack of application in rural grid contexts.
    - Insufficient consideration of socio-economic factors affecting rural energy consumption.
- **Suggested Improvements**:
    - Tailor models to account for rural-specific variables.
    - Integrate socio-economic data to enhance forecasting accuracy.

---

3. Improved Electric Load Forecasting Using Quantile Long Short-Term Memory (LSTM) Networks

- **Authors**: [Authors not specified]
- **Published in**: *Energy Reports* (Elsevier), 2025
- **Link**: ScienceDirect Article
- **Summary**: This paper introduces a quantile LSTM approach for electric load forecasting, offering probabilistic predictions that can better capture uncertainty in energy demand.ScienceDirect
- **Research Gaps**:
    - Application in rural grids remains unexplored.
    - Challenges in implementing such models where data granularity is low.
- **Suggested Improvements**:

- Adapt the quantile LSTM model for use with coarser, less granular data typical of rural grids.
- Combine with data augmentation techniques to enhance model training.

---

4. Forecasting Energy Demand in Isolated Rural Communities

- **Authors**: [Authors not specified]
- **Published in**: *Energy for Sustainable Development* (Elsevier), 2021
- **Link**: ScienceDirect Article
- **Summary**: This study focuses on forecasting energy consumption demand of customers in smart grids using Temporal Fusion Transformer (TFT), highlighting its applicability in isolated rural communities.ScienceDirect+1ScienceDirect+1
- **Research Gaps**:
  - Limited case studies from Bangladesh.
  - Need for models that can be trained with minimal data.ScienceDirect
- **Suggested Improvements**:
  - Conduct localized studies within Bangladesh to validate model effectiveness.
  - Develop lightweight models suitable for deployment in resource-constrained environments.

🔍 Identified Research Gaps & Needed Improvements

- **Data Scarcity**: Many rural areas lack high-resolution energy consumption data, making it challenging to train complex models.
- **Model Complexity**: Advanced models like deep learning require significant computational resources, which may not be feasible in rural settings.

- **Contextual Factors**: Socio-economic and cultural factors influencing energy consumption in rural Bangladesh are often overlooked.
- **Deployment Challenges**: Implementing and maintaining sophisticated forecasting models in rural areas can be hindered by limited technical expertise and infrastructure.

]

---

6. Comments / Suggestions

- Consider focusing on **specific PBS regions** (e.g., Gazipur or Cumilla) for realistic modeling.
- Include synthetic scenario modeling for high/low demand seasons.
- Add benchmarking with global datasets for broader comparison.
- Optional: Integrate renewable energy contribution forecasts (if time permits).
