**Internship Completion Report**

**“Time Series and Long Short-Term Memory Based Models for Prediction of Load Demand Data”**

**16th May 2024 to 30th June 2024**

**Submitted by:**

Aryan Soni

Roll no: 22111009

Department of Biomedical Engineering

**Under the guidance of respected**

**Professor (HOD):**

Dr. (Mrs.) Anamika Yadav Mam

Department of Electrical Engineering

**Introduction:**

During my internship in the Electrical Department, under the guidance of respected professor (HOD) Anamika Yadav Mam, I had the invaluable opportunity to delve into the domain of time series forecasting. My primary focus was on applying and comparing various forecasting models, including advanced neural network architectures of deep learning methods like CNN, LSTM, and RNN, as well as traditional statistical methods such as ARIMA and SARIMA. This comprehensive exploration allowed me to develop a robust understanding of how different models perform under varying conditions. Emphasizing ARIMA and SARIMA models, I gained significant insights into their efficacy in capturing seasonal trends and making accurate short-term forecasts. This internship has not only enriched my technical skills but also provided me with a deeper appreciation for the complexities and applications of time series forecasting in the field of engineering and science.

**Internship Details:**

I joined the Electrical Department as an intern for a two-month period, eager to apply my theoretical knowledge in a practical setting. The Electrical Department, renowned for its cutting-edge research and innovative projects, focuses on a wide array of areas including power systems, control systems, and signal processing. Under the mentorship of respected Professor **Anamika Yadav mam**, I was integrated to get hands-on experience in time series forecasting. The department's collaborative environment and state-of-the-art facilities provided an excellent backdrop for my learning and development, allowing me to engage deeply with both the theoretical and practical aspects of electrical engineering.

**Learning Outcomes:**

Throughout my internship, I acquired a wealth of knowledge and skills that have significantly enhanced my expertise in engineering. I became proficient in advanced MATLAB functions and utilized various toolboxes for deep learning, enabling me to implement complex forecasting models. My hands-on experience with different mathematical models, particularly those used for advanced time series forecasting, has broadened my analytical capabilities. Additionally, I immersed myself in the latest research by reading numerous scholarly papers, which provided a deeper understanding of current trends and innovations in the field. This comprehensive learning experience has equipped me with both the theoretical foundation and practical skills necessary for tackling real-world forecasting challenges.

**Tasks and Solutions:**

During my internship, I encountered several challenges that tested my problem-solving skills and deepened my understanding of forecasting models. One significant challenge was managing training and testing errors, which required meticulous parameter tuning and model validation to achieve accurate predictions. Additionally, I faced mathematical errors that arose from the complexity of the models, necessitating a thorough review of the underlying algorithms and implementation. Selecting the most appropriate model for forecasting was another hurdle, given the diverse nature of the data and the specific requirements of each project. To address these challenges, I employed a systematic approach: iterative testing and optimization for error reduction, in-depth analysis and troubleshooting of mathematical issues, and comprehensive model evaluation to ensure the best fit for the data. These experiences have sharpened my technical acumen and prepared me for future complex forecasting tasks.

**LSTM Model for Electricity Load and Demand Forecasting:**

During my internship, I focused on utilizing Long Short-Term Memory (LSTM) models for forecasting electricity load and demand, a crucial aspect of energy management systems. LSTM networks, a special class of recurrent neural networks (RNNs), are designed to capture long-term dependencies in time series data. This capability is especially beneficial for electricity load forecasting, where patterns and dependencies span across different time horizons.

Electricity load forecasting involves predicting future electricity demand based on historical consumption data. Traditional methods, such as ARIMA, may struggle with the complex, non-linear patterns present in electricity consumption data. LSTMs address these challenges by using memory cells that can retain information over extendedperiods. Each memory cell in an LSTM network contains three gates: input, output, and forget gates. These gates regulate the flow of information, allowing the network to selectively remember

forget information as needed, thus preventing issues like vanishing or exploding gradients that are common in standard RNNs.

To implement the LSTM model, I began by pre-processing the historical electricity load data to ensure it was clean and suitable for training. This involved normalizing the data and creating appropriate time lags to capture temporal dependencies. I then designed the LSTM architecture, tuning hyperparameters such as the number of layers, the number of neurons per layer, the learning rate, and the batch size. The model was trained using backpropagation through time (BPTT), a variant of the standard backpropagation algorithm adapted for training RNNs.

Throughout the training process, I evaluated the model's performance using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The LSTM model demonstrated superior performance compared to traditional models, effectively capturing the intricate patterns in the electricity load data. I also implemented various techniques to prevent overfitting, such as dropout regularization and early stopping, ensuring the model's generalizability to unseen data.

The results of the LSTM model were promising, showcasing its ability to accurately predict both short-term and long-term electricity demand. This accurate forecasting is critical for the efficient operation of power systems, allowing utility companies to balance supply and demand, reduce operational costs, and enhance grid stability. Moreover, the use of LSTM networks in this context underscores the potential of deep learning models to revolutionize traditional forecasting methods in the energy sector.

In addition to the technical aspects, I delved into the existing literature on LSTM applications in load forecasting. Studies have consistently highlighted the efficacy of LSTM networks in handling the non-linearity and temporal dependencies inherent in electricity load data. For instance, researchers have found that LSTM models outperform other machine learning algorithms, including support vector machines and feedforward neural networks, in various load forecasting scenarios. This body of work provided a solid theoretical foundation and reinforced the practical significance of my internship project.

Overall, working with LSTM models for electricity load forecasting has been a profound learning experience. It has not only deepened my understanding of advanced neural networks but also demonstrated the transformative impact of these technologies on real-world applications in engineering.

**SARIMA Model for Electricity Load and Demand Forecasting:**

Load forecasting has progressively become a crucial component of the energy management system. This study presents a powerful methodology for short term load forecasting with the help of previous load trends. ARIMA has limitations in handling seasonality directly, which led to the development of SARIMA (Seasonal ARIMA). SARIMA extends ARIMA by incorporating seasonal differencing and seasonal autoregressive and moving average terms, making it more adept at modelling seasonal patterns within the data.

Electrical system requires a subtle balance equilibrium and demand., which affects the demand for electrical energy. Additionally, the push for a sustainable grid that integrates renewable energy sources and electric vehicle technology to reduce pollution emissions add to the existing imbalance. Therefore, accurate demand estimation becomes crucial in improving system reliability, security and mitigating the differences. Load forecasting, an important component of the smart grid, has gained significant attention from researchers. It is categorized into various types based on the forecasting timeframe, including short-term load forecasting (STLF). Different forecasting purposes attracted increasing research interest and exploration in load field. Combining ARIMA with learning methods like LSTM or CNN aim to enhance forecasting accuracy by capturing both linear and non-linear patterns.

Despite many advancements, SARIMA often remains superior for many practical applications due to its interpretability, robustness, and effectiveness in handling seasonality. Unlike complex deep learning models, SARIMA provides clear insights into seasonal and trend components, making it easier to diagnose and refine. Additionally, SARIMA requires less computational power and training data, which is advantageous in many real-world scenarios. Estimating the electric power generated so that it is the same as that consumed is also part of the forecasting study. An imbalance in electrical power will result in blackouts or otherwise a waste of electrical energy. Many works discuss the techniques and methods used in forecasting methods. Some of them are linear regression time series approaches and AI-ML such as ANN and fuzzy logic design patterns. Here, Forecasting is used to predict upcoming electrical loads value, for optimum balance of electrical power in the generation control system and actual demand.

**Literature Overview:**

1. Seasonality Handling: Electricity load data typically exhibit strong seasonal patterns, with variations depending on the time of day, week, or year. The application of this seasonal pattern has been developed into a double seasonal pattern.

2. Interpretability: SARIMA models are relatively straightforward to interpret compared to complex machine learning models like LSTMs or CNNs. This interpretability is crucial for utility companies and policymakers who need to understand and trust the forecasts to make informed decisions.

3. Data Efficiency: SARIMA models require less data to train effectively compared to deep learning models, which need large datasets to capture patterns accurately. In many cases, historical electricity load data may not be extensive enough to train complex models effectively, making SARIMA a more practical choice.

4. Computational Efficiency: SARIMA models are less computationally intensive than deep learning models [10]. This efficiency makes SARIMA suitable for real-time forecasting where quick updates are essential.

5. Robustness and Reliability: SARIMA models are robust and provide reliable forecasts even in the presence of noise and outliers in the data. This reliability is critical for electricity load forecasting, where inaccurate predictions can lead to significant operational and financial consequences.

6. Combination of Trend and Seasonality: SARIMA combines trend and seasonal components seamlessly, allowing it to capture both long-term trends and short-term seasonal variations in electricity load data. This holistic approach enhances the accuracy of forecasts.

While advanced models like LSTM, CNN, and hybrid models can capture complex non-linear relationships and long-term dependencies, they often come at the cost of higher complexity and require more data and computational resources. These models might outperform SARIMA in specific cases, particularly where non-linear patterns dominate, but the balance of interpretability, efficiency, and effectiveness makes SARIMA a preferred choice for many electricity load forecasting applications.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model addresses this limitation by incorporating seasonal components, extending the ARIMA framework. SARIMA introduces parameters for seasonality, enabling it to model periodic fluctuations and trends. This paper explores the application of the SARIMA model for signal prediction, demonstrating its ability to accurately forecast seasonal and non-seasonal data. By comparing SARIMA with ARIMA and other models, we highlight its superior performance and practical implications, providing valuable insights for practitioners in various fields.

**Methodology:**

The SARIMA model operates by:

1. Differencing the time series to achieve stationarity, using both non-seasonal (d) and seasonal (D) differencing.
2. Applying autoregressive (AR) and moving average (MA) components to the differenced series to model the underlying process.
3. Including seasonal AR (SAR) and seasonal MA (SMA) terms to capture seasonal dependencies.

Now let us understand the true meaning of regression:

In the SARIMA (Seasonal Autoregressive Integrated Moving Average) model, the autoregressive (AR) component models the relationship between a variable and its own past values, considering both seasonal and non-seasonal influences, means a mathematical relationship between the variable and the values which occurred in the function in earlier time. A time series is according to regular order of time stamps.

We have many advantages using the regression parameter as,

1. Modelling Relationships: Regression models capture how changes in predictors relate to changes in the target variable. This allows forecasters to understand and quantify the influence of various factors on the outcome of interest.
2. Prediction: Once a regression model is trained on historical data, it can be used to predict future values of the dependent variable based on new values of the independent variables. This predictive capability is essential for forecasting future trends or outcomes.
3. Scenario Analysis: Regression models enable scenario analysis by exploring how changes in one or more predictors would affect the forecasted outcome. This helps decision-makers assess different strategies or interventions before implementation.
4. Assessment of Impact: By quantifying the relationship between predictors and the target variable, regression helps forecasters assess the impact of external factors or interventions on future outcomes. This is crucial for planning and decision-making.
5. Model Evaluation: Regression provides a framework for evaluating the significance and contribution of each predictor variable to the forecast. This evaluation helps in selecting the most relevant variables and refining the forecasting model.
6. Uncertainty Estimation: Regression models can also estimate the uncertainty or confidence intervals around the forecasts, providing insights into the reliability of the predictions and potential risk.

**Result:**

We have demonstrated the effective application of the Seasonal Autoregressive Integrated Moving Average (SARIMA) model for forecasting electricity load data. The SARIMA model, renowned for its capacity to manage seasonality and non-stationary characteristics, has shown significant reliability in predicting electricity demand.

Our empirical results highlight the SARIMA model's proficiency in capturing the intricate seasonal patterns and underlying trends in electricity load data. This precision is crucial for operational planning and energy management, ensuring that supply meets demand with minimal discrepancies. The performance metrics affirm the model's accuracy, with forecasting errors maintained within stringent engineering standards.

The engineering community can greatly benefit from the SARIMA model's adaptability, applying it to various time series datasets with seasonal fluctuations. This versatility makes SARIMA a robust tool for engineers tasked with optimizing systems based on accurate predictive analytics.

Looking forward, future research could enhance the SARIMA model's forecasting capability by integrating it with advanced machine learning techniques, potentially improving its precision and adaptability. Additionally, incorporating exogenous variables such as weather data and economic indicators could provide a more comprehensive and dynamic forecasting framework, further aligning with engineering best practices.

**Feedback and Reflection:**

The feedback I received from mam was overwhelmingly positive and constructive. Their observations highlighted my progress in mastering advanced forecasting models and my ability to apply theoretical knowledge to practical challenges. This internship has been a transformative experience, allowing me to reflect on my strengths and areas for improvement. I have realized the importance of continuous learning and adaptation in the ever-evolving field of forecasting. The challenges I faced and the solutions I devised have boosted my confidence and problem-solving capabilities. This experience has reinforced my passion for time series forecasting and has set a solid foundation for my future work in this field. I am grateful for the opportunity to contribute to meaningful projects and to learn from some of the best minds in the industry.

**Conclusion:**

I would like to extend my deepest gratitude to Professor Dr. Anamika Yadav mam, whose guidance and support were instrumental throughout my internship. Her expert mentorship not only provided invaluable insights into the intricacies of time series forecasting but also significantly broadened my problem-solving skills. Mam was always available to help me navigate challenges, offering constructive feedback and encouraging me to explore innovative solutions. Her dedication to fostering a collaborative and enriching learning environment has been a cornerstone of my growth during this internship. I have significantly enhanced my technical skills and understanding of time series forecasting. The challenges I encountered and the solutions I developed have fortified my problem-solving abilities and prepared me for future works. The support and mentorship I received have been instrumental in my growth, both professionally and personally. This internship has solidified my career aspirations and equipped me with the knowledge and skills to excel in the field of forecasting and deep learning. I am immensely grateful for this opportunity and look forward to applying what I have learned in my future projects and study. I am immensely thankful for her unwavering support and the profound impact she has had on my academic and professional journey.