A STUDY ON PREDICTIVE ANALYTICS FOR TELECOMMUNICATION NETWORK DATA FORECASTING

by

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in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

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Abstract

The telecommunications industry is experiencing rapid and exponential development, driven by complex changes in the network infrastructure that mirror evolving customer expectations. Despite a substantial body of research, with more than 6.3 million publications, telecommunications forecasting lacks standardized integration between theoretical models and practical applications. This research presents a systematic policy-driven framework that provides a structured solution to the challenges of telecommunications forecasting throughout the entire data selection process evaluation chain.

We analyze a large, real-world dataset spanning twelve months, from September 2022 onward, collected from multiple adjacent geographical regions with distinct operational profiles. Area 1 operates 129 base stations in 643 cells, while Area 2 operates 99 base stations in 613 cells. In particular, despite its smaller footprint, Area 2 delivers 25% greater downlink throughput and supports traffic volume 30% above its local capacity requirements. The complete data set, which contains no missing values for key performance indicators, provides unparalleled insight into network performance under diverse operational scenarios.

Our study employs rigorous experimentation and analysis to uncover advanced findings regarding both data pre-processing techniques and model performance evaluation. The experimental results demonstrated that the Gated Recurrent Unit (GRU) achieved superior user prediction results, with an R-squared of 0.929 and low error ranges (MSE: 0.000174–0.012039, MAPE: 1.23%–14.00%). A Long Short-Term Memory (LSTM) network achieved notable success in traffic forecasting, with an R-squared of 0.879 and a MAPE of 10.83%, outperforming traditional ARIMA models, which consistently yielded negative R-squared values.

Among advanced fusion architectures, our innovative Hierarchical-LSTM proved superior, achieving an exceptional R-squared of 0.9677 and minimal error rates (MSE: 0.0008, MAPE: 5.05%). This performance surpassed other sophisticated models, including self-attention-based (R-squared: 0.9602) and Hybrid 2-Layer (R-squared: 0.956) approaches. These fusion models outperformed those that integrate ARIMA, yielding negative R-squared values.

The analysis of data granularity yielded key findings essential for developing real-world implementation strategies. Area-level forecasting consistently outperformed lower-level (cell-level) forecasts in all metrics. Quantitative analysis revealed significantly lower MSE values for area-level predictions: for user predictions (ARIMA: 0.009 versus 0.075 cell level, LSTM: 0.004 versus 0.030 cell level), throughput predictions (ARIMA: 0.062 versus 0.122 cell level, LSTM: 0.028 versus 0.046 cell level), and traffic predictions (ARIMA: 0.008 versus 0.059 cell-level, LSTM: 0.004 versus 0.015 cell level). Support Vector Machines demonstrated exceptional predictive capabilities at the area level, with MSE values reaching 0.001 for user and traffic prediction outcomes.

Our research evaluated the impact of combinations of feature variants on prediction

outcomes using novel correlation analysis methods. User count and traffic volume exhibited the strongest synergistic relationship (correlation: 0.899, R-squared: 0.879 with the DL_TRAFFIC_MB variant). Although throughput maintained robust performance across variants, the analysis revealed that using only throughput and user count features resulted in poor forecast accuracy (R-squared: -5.630 and -3.748, respectively), while incorporating additional characteristics improved accuracy (R-squared: 0.889 baseline, 0.822 with the traffic variant).

Data preprocessing analysis identified optimal configuration parameters, with Min-Max scaling achieving superior normalization performance (R-squared: 0.931) compared to other techniques. Optimal model performance was achieved with a 42% training data split. Prediction accuracy decreased substantially with 20% and 90% split ratios (R-squared: 0.033 and 0.323, respectively). Investigating temporal patterns demonstrated that weekly seasonality significantly improved prediction accuracy across network elements (throughput R-squared: 0.923, user R-squared: 0.887). Systematic hyperparameter tuning revealed that the RMSprop optimizer with a batch size of 32 outperformed the Adam optimizer with a batch size of 64 (R-squared: 0.767).

We introduce a novel framework that advances telecommunications forecasting by uniquely combining theoretical methods with practical implementation knowledge. Our framework integrates rigorous model selection processes with domain expertise for dataset and feature selection, while implementing privacy-preserving techniques to bridge the gap between abstract methodologies and real-world applications. Through comprehensive data analysis, we revealed crucial relationships between user behavior patterns and network traffic characteristics, establishing that multi-feature approaches with area-level predictions achieve optimal results.

This comprehensive framework represents a significant advancement in telecommunications forecasting, establishing theoretical foundations that enhance both academic research and industry practice.

Keywords: Forecasting — Network — Policy — Guideline -Telecommunication — Network KPI - Time Series Analysis — LSTM — GRU — SVM — Fused Mode

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Firstly, all praise to the Great Allah for whom my thesis has been completed without any major interruption. Secondly, to my advisor Md. Golam Robiul Alam sir for his kind support and advice in my work. He helped me whenever I needed help. And finally, to my family without their throughout support it may not be possible. With their kind support and prayers, I am now on the verge of my graduation.

***Data Confidentiality Statement...
The network performance data presented in this study has been anonymized. All identifying information related to specific telecommunications operators, network configurations, and proprietary technologies has been removed or modified to protect commercially sensitive information while maintaining the integrity of the research findings.

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Chapter 1

Introduction

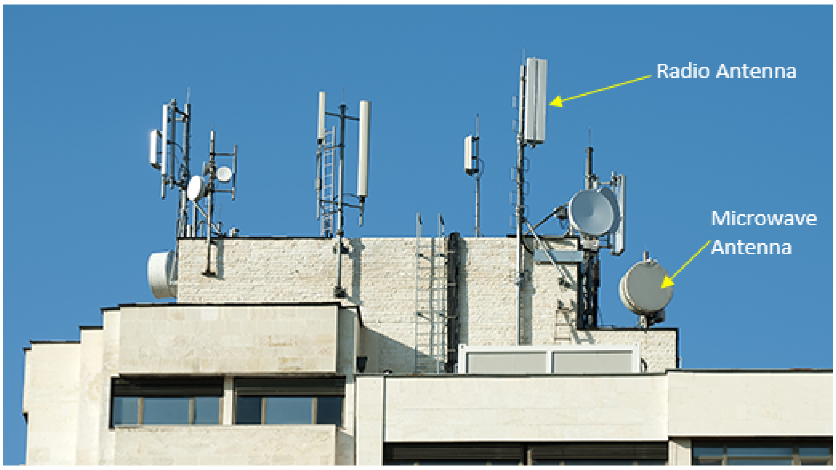

Figure 1.1: A Telecom Site Tower

When we think about a telecom site[9], the pictures as shown in figure 1.1 comes in our mind. These are actually telecom antennas (similar to the router antennas that we have in our home). There are two type of antennas are here, radio antenna and microwave antenna. Radio antennas are responsible for transmittting and receiving signals with UE (mobile phones, tablets, vehicle trackers etc). It is a part of a site, which consists of one or more sectors. Each sector can have one or multiple cells, which represent a geographical area covered by a single base station, or cell site. And microwave antennas are used connect one site with other.

These physical infrastructure components form the foundation for delivering a comprehensive range of telecommunications services that have become integral to modern society. As illustrated in Figure 1.2, telecommunications networks enable critical services across multiple domains, from essential mobile communications and internet connectivity to advanced applications in entertainment, enterprise solutions, and smart city development. This convergence of services demonstrates how telecommunications has evolved beyond its traditional role of voice and data transmission, becoming a catalyst for digital innovation across industries. The network's ability to support diverse applications, from real-time video streaming to IoT sensor networks, showcases its fundamental role in enabling digital transformation and societal advancement.

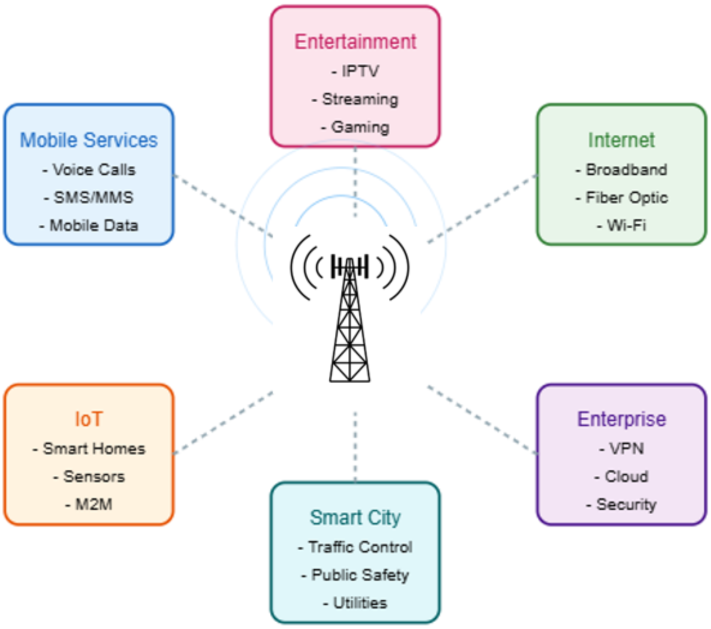

Figure 1.2: Applications of Telecommunication

The remarkable growth of the telecommunications industry has been accompanied by increasingly intricate network architectures and evolving customer demands, necessitating sophisticated approaches to network optimization and resource allocation. As highlighted by Challita et al. [51], the integration of machine learning into wireless cellular networks has revolutionized deployment strategies and applications, creating new opportunities for advanced predictive analytics. This evolution has spawned various forecasting methodologies, each attempting to address specific aspects of telecommunications challenges.

The diversity in forecasting approaches reflects the multifaceted nature of telecommunications prediction requirements. Studies in customer behavior prediction demonstrate this variety, employing methods from Decision Trees and Logistic Regression to Neural Networks and Support Vector Machines. As emphasized by [61] in their comprehensive survey of network traffic forecasting, this methodological diversity, while providing flexibility, has created significant challenges in selecting and implementing appropriate forecasting techniques for specific telecommunications contexts.

The absence of a unified framework becomes particularly apparent when considering the various aspects of telecommunications forecasting that must work in harmony. Different prediction granularities, from cell-level to area-level forecasts, require different approaches, while data privacy concerns must be balanced against the need for accurate predictions. Rapid technological advancement in the industry further complicates this landscape, demanding forecasting methods that can adapt to emerging network technologies while maintaining prediction accuracy.

This thesis aims to bridge these gaps by providing a comprehensive analysis of the forecasting pipeline specifically tailored for telecommunications data. By examining variations in data preprocessing, feature engineering, model selection, and evaluation techniques, we will establish a holistic framework that addresses the unique challenges of telecom forecasting. Drawing from established methodologies and emerging techniques discussed in [52] and [55], this research will offer telecommunication providers and forecasters a 360-degree perspective on predictive modeling. Our framework will encompass various aspects of telecommunications forecasting, from network traffic patterns to customer behavior predictions, enabling organizations to make more informed decisions about infrastructure planning, resource allocation, and service optimization. This comprehensive approach will not only benefit telecommunications operators, but also provide valuable insights for forecasters across different domains facing similar complexity in their predictive modeling endeavors.

1.1 Research Challenges

Forecasting in the telecommunications sector presents unique challenges due to the inherent complexity of telecom networks, the volume of data generated, and the dynamic nature of network behavior. Despite considerable advancements in forecasting techniques, several key research gaps remain unaddressed, which hinder the development of robust and reliable forecasting methodologies for telecommunications. These gaps primarily revolve around data handling, domain expertise integration, model adaptability, and performance evaluation.

One of the most significant research gaps lies in the lack of standardized guidelines for forecasting in telecom. Forecasting methodologies are often developed on an ad hoc basis, with little consistency in the approaches to data selection, preprocessing, and modeling. The absence of such guidelines results in disparate and non-replicable findings, making it difficult to establish generalizable best practices for telecom forecasting. Researchers and practitioners are left navigating a fragmented landscape without clear direction, which slows the progress of innovation in this critical area.

Another key gap is the limited incorporation of telecom domain knowledge into forecasting models. Telecom networks are inherently hierarchical, with data generated at multiple levels—such as site, cell, and area levels. These networks also exhibit complex interdependencies among metrics like throughput, traffic volume, and user count. While forecasting algorithms excel at identifying patterns in data, their effectiveness in telecom forecasting is often constrained by a lack of domain-specific insights. The failure to fully leverage domain expertise has led to models that may be technically sound but lack operational relevance or practical utility for telecom stakeholders.

Scalability and adaptability represent additional gaps in the forecasting domain. With the advent of advanced technologies like 5G, IoT, and edge computing, telecom networks are becoming increasingly complex and data-intensive. Existing forecasting models often struggle to scale to the size and speed of modern telecom datasets, and many lack the flexibility to adapt to rapidly changing network conditions. This inability to handle evolving network behaviors poses a significant challenge for maintaining forecasting accuracy in real-world applications.

Another notable gap is the inconsistency in the evaluation metrics used to assess forecasting performance. While numerous metrics are available, such as Mean Squared Error (MSE) and R-squared, there is no universal standard for evaluating forecasting models in telecom forecasting. This lack of standardization creates ambiguity, making it difficult to compare results across studies and identify the most effective approaches. Without a clear framework for evaluation, the reliability and utility of forecasting models remain uncertain.

Finally, there is a persistent gap in addressing the challenges of data privacy and security. Telecom forecasting involves processing sensitive network and user data, raising concerns about protecting this information while ensuring accurate predictions. Current methodologies rarely focus on privacy-preserving techniques, leaving an important aspect of forecasting largely unexplored.

1.2 Research Objectives

In this research, we have addressed several of these critical gaps. We developed comprehensive guidelines for data selection, demonstrating that area-level data provides the most reliable forecasts for general applications, while detailed methods were established for cell and site-level forecasting. By integrating telecom domain knowledge into the feature selection process, we enhanced the practical relevance and predictive accuracy of forecasting models.

Our work also tackled scalability by optimizing data splitting ratios and employing advanced forecasting models like fused and attention based models, which demonstrated superior performance even in large-scale, dynamic networks. Additionally, we standardized the evaluation process by validating R-squared as a consistent and reliable metric for assessing model performance across telecom forecasting scenarios.

We've made great progress, but there's more to explore. Future research should include 5G, IoT, and factors like lunar cycles and holidays. Expanding beyond telecommunications could also be valuable. Collaboration among operators, vendors, service providers, and regulators is crucial to develop scalable, privacy-preserving, and robust forecasting methods. This will help us keep up with the fast-evolving tech landscape and adapt to new challenges and opportunities.

1.3 Research Contributions

Our research has yielded eleven significant contributions to telecommunications forecasting methodology:

Through extensive analysis and rigorous evaluation of prediction accuracy across different network hierarchies [55], we establish definitive guidelines for dataset selection in telecommunications forecasting. Our research demonstrates that area-level data consistently outperforms cell or site-level data for general forecasting purposes. For specific scenarios requiring cell and site-level forecasting, we provide detailed methodologies, including approaches for incorporating adjacent cell and site performance metrics.

Our research validates the fundamental importance of expert domain knowledge in the feature selection process [31]. Through systematic analysis, we demonstrate that features identified as key indicators of customer satisfaction and network performance consistently produce more reliable predictions compared to basic traffic metrics. The results particularly emphasize the superiority of network quality metrics, such as data speed and throughput, over traditional quantity-based metrics like user count or traffic volume.

Through systematic testing of different normalization approaches, we demonstrate that modifications in normalization techniques alone can improve model performance by up to 44%, highlighting the significant impact of proper data preprocessing on forecasting accuracy. Apart from this, we establish the effectiveness of data normalization techniques in protecting sensitive network information while maintaining forecasting accuracy [50]. This addresses a crucial concern in telecommunications operations, where the need to protect sensitive network data often conflicts with the requirement for accurate predictions.

Our comprehensive testing of data splits ranging from 10% to 90% identifies that ratios between 30% to 70% consistently provide better accuracy for telecom network forecasting applications [61]. This contribution provides clear guidelines for data partitioning in model development.

We demonstrate that while statistical models like ARIMA are inadequate for current complex & large telecom data patterns, LSTM and GRU architectures show superior performance [52]. Most significantly, we establish that combined models achieve the best results for telecommunications data.

Our investigation reveals that stacked two-layer models and self-attenuation based compound models achieve exceptional performance, exceeding 90% accuracy in telecom network forecasting [64]. This finding provides clear direction for implementing advanced forecasting architectures.

We quantify the impact of different seasonality patterns, demonstrating that weekly seasonality consistently outperforms monthly patterns, achieving improvements of 1.73%, 7.52%, and 15.50% for traffic, throughput, and user count respectively.

Our research establishes effective methodologies for integrating correlated variants into forecasting models [38]. Results show that highly correlated variants enhance model accuracy, while slightly less correlated variants can degrade performance, providing clear guidelines for feature engineering.

We demonstrate the critical impact of hyperparameter tuning, achieving a 265% improvement in MSE and elevating R-squared values from -60.8 to 0.76 through systematic optimization approaches.

We establish R-squared values as the most reliable metric for accuracy measurement

[49], demonstrating consistency across both normalized and original data scales, unlike other metrics that can vary dramatically (from 0.0394 to 285125.4406) based on data magnitude. This consistency enables clear distinction between unfit (-0.1588) and well-performing (0.9287) models.

These contributions collectively provide a comprehensive framework for implementing and optimizing forecasting systems in telecommunications networks, representing a significant advancement in bridging theoretical research with practical implementation.

1.4 Experimental Scenario and Methodology

1.4.1 Experimental Scenario:

For our experiment, we have collected real-world data from four different areas over one year, as shown in Figure 1.3. These areas, including both urban and suburban environments, exhibit a diverse range of performance characteristics. The adjacent selection of these areas facilitates a specific scenario analysis, which will be described in the methodology section. These data were then converted to cell and site levels to provide a comparative analysis. The diversity in both geographic classification (urban versus suburban) and performance characteristics ensures that our dataset captures a wide range of real-world scenarios, strengthening the applicability and reliability of our findings. Each area exhibits distinct usage patterns and challenges, providing a rich basis for comparative analysis and methodology validation.

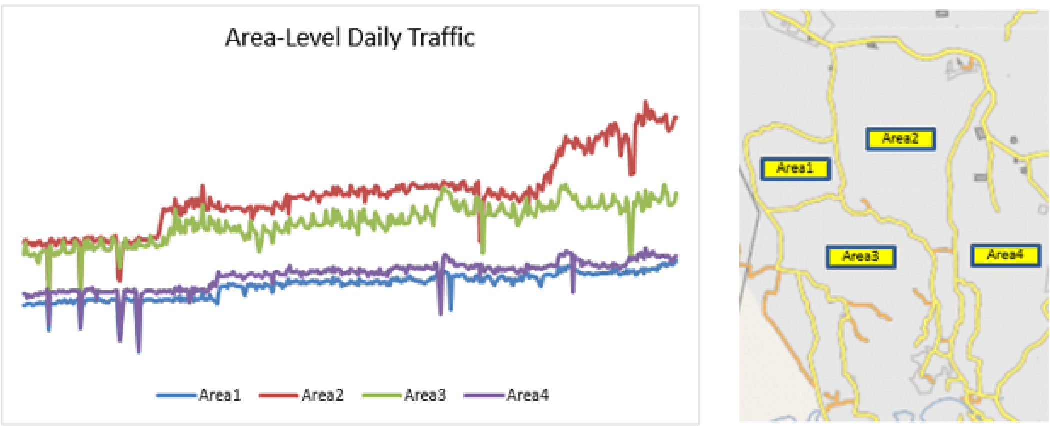

Figure 1.3: Experimental Scenario

1.4.2 Methodology:

Figure 1.4 shows the simplified block diagram of the methodology applied for the research. It begins with Network Data Input (raw network metrics), processed through a Data Transformation (multi-technique data preparation) and Model Enhancement (advanced model development), evaluated via Performance Analysis (metric evaluation and selection), ultimately producing an Optimized Model Output (deployment-ready forecasting solution).

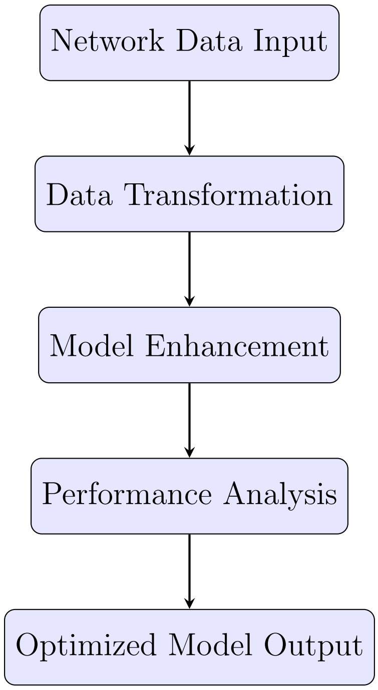

Figure 1.4: Simplified Block Diagram of Methodology

Network Data Input: Raw network data, as mentioned above, is collected from real network which is the foundation for predictive modeling.

Data Transformation: A comprehensive data preparation process integrating multiple techniques for optimal data quality. This includes comparative analysis of cell-level, site-level, and area-level data points, systematic implementation of various normalization methods like Min-Max Scaling, Z-score normalization, and Robust Scaling. The pipeline incorporates strategic dataset division into training, validation, and testing sets with various split ratios to ensure model generalization capabilities.

Model Enhancement: An advanced model development framework incorporating multiple machine learning and deep learning approaches. The suite systematically explores ARIMA, SVR, LSTM, and GRU architectures, implementing ensemble learning techniques through bagging, boosting, and stacking for multivariant analysis. It employs Grid Search for hyperparameter optimization while integrating seasonal pattern analysis to enhance forecasting accuracy across different time intervals and variable combinations.

Performance Analysis: A rigorous evaluation framework implementing comprehensive metric selection and analysis. The process carefully evaluates model performance through multiple metrics including MSE, RMSE, MAPE, MAE, and R-squared, enabling thorough comparison across different model configurations. This systematic assessment helps identify the most suitable evaluation metrics for specific prediction scenarios, ensuring balanced and accurate performance measurement across diverse network conditions.

Optimized Model Output: The final validated model demonstrates superior forecasting accuracy and stability across diverse datasets. This output represents the culmination of iterative optimization processes, producing a deployment-ready solution that effectively predicts network behavior and reduces alarms while maintaining high accuracy standards and practical applicability in real-world scenarios.

1.5 Scope and Limitation

Our research confronts several fundamental limitations that shape both its applicability and future directions. The most significant limitation stems from the inherent tension between standardization and innovation in policy-driven approaches. While our framework provides structured guidelines for telecommunications forecasting, this very structure could potentially constrain innovation in rapidly evolving technological environments. This limitation reflects a conscious trade-off between providing clear, actionable guidance and maintaining flexibility for emerging methodologies.
In terms of temporal analysis, we deliberately focused our research on weekly and monthly seasonality patterns, as these represent the most common temporal cycles in telecommunications network behavior. This scope decision, while practical, means our framework provides limited guidance for other significant temporal patterns such as lunar cycles, holiday effects, or special event impacts. Organizations dealing with these additional patterns may need to extend our framework to accommodate their specific requirements.
Our framework demonstrates particular strength in area-level forecasting but offers more limited direction for cell and site-level predictions. This limitation emerges from the inherent complexity of micro-level forecasting, where local factors and interdependencies between adjacent cells create additional layers of complexity. While we provide foundational guidance for these scenarios, practitioners working with very granular predictions may need to supplement our framework with additional domain-specific considerations.
These limitations suggest promising directions for future research. The framework could be extended to incorporate emerging technologies like 5G and IoT, expanding its applicability to new telecommunications paradigms. More comprehensive guidelines for cell and site-level predictions could be developed to address the current limitations in micro-level forecasting. The exploration of lunar and holiday seasonality patterns would enhance the framework's temporal analysis capabilities. Additionally, investigating applications beyond telecommunications could reveal new opportunities for adapting our methodology to different domains.
Despite these limitations, our framework provides a robust foundation for telecommunications forecasting that can be adapted and extended as technology and requirements evolve. The acknowledgment of these constraints helps practitioners understand the framework's boundaries while suggesting paths for future development and enhancement. Through continued research and practical application, these limitations can be systematically addressed, further strengthening the framework's utility in telecommunications forecasting.

1.6 Thesis Organization

The thesis structure follows a systematic approach to research, as illustrated in Figure 1.5. It begins with the **Introduction**, setting the stage for the study. The **Literature Review** establishes the theoretical foundation, followed by an exploration of **Mobile Networks and KPIs**, which provides the necessary technical background.

The research methodology is outlined in the **Methodology** chapter, while the **Experimental Design and Data Analysis** section describes the research approach and implementation. The findings are presented in **Results and Performance Evaluation**, leading to a summary of key insights in the **Conclusion**. The thesis concludes with **References**, ensuring a comprehensive academic document that progresses logically from theoretical concepts to practical outcomes in network performance analysis.

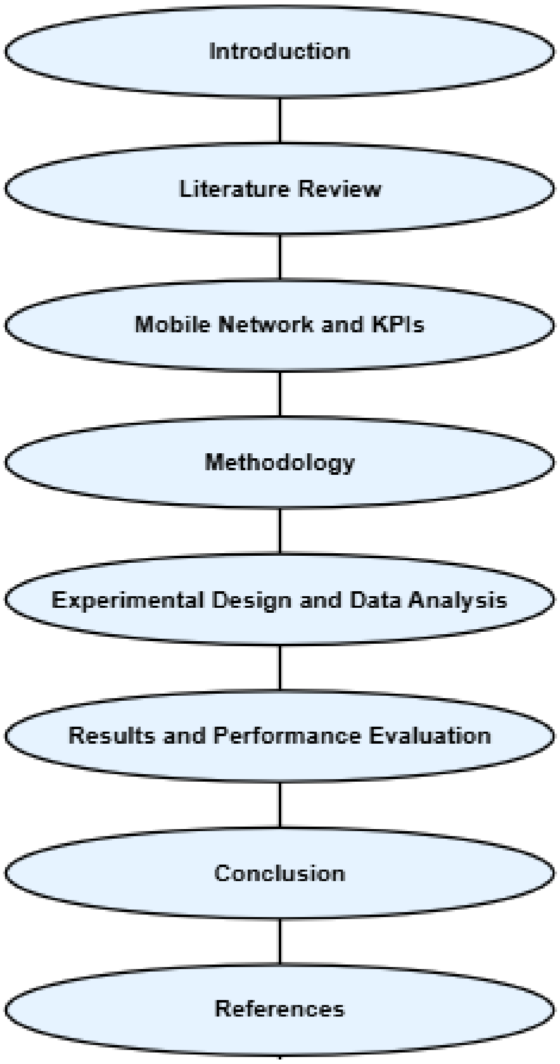

Figure 1.5: Outline of the Study

Chapter 2

Literature Review

The integration of AI into telecommunications represents more than just technological advancement; it signifies a paradigm shift in how networks are designed, operated, and evolved. As we move beyond 5G, this partnership between telecommunications and AI continues to deepen, promising even more sophisticated solutions for network automation, service personalization, and industry-specific applications. The future of telecommunications lies in this symbiotic relationship, where AI-driven insights and adaptability combine with advanced communication infrastructure to create increasingly intelligent and responsive networks capable of meeting the ever-growing demands of our connected world.Figure 2.1 shows the evoluation of telecommunication and AI-ML.

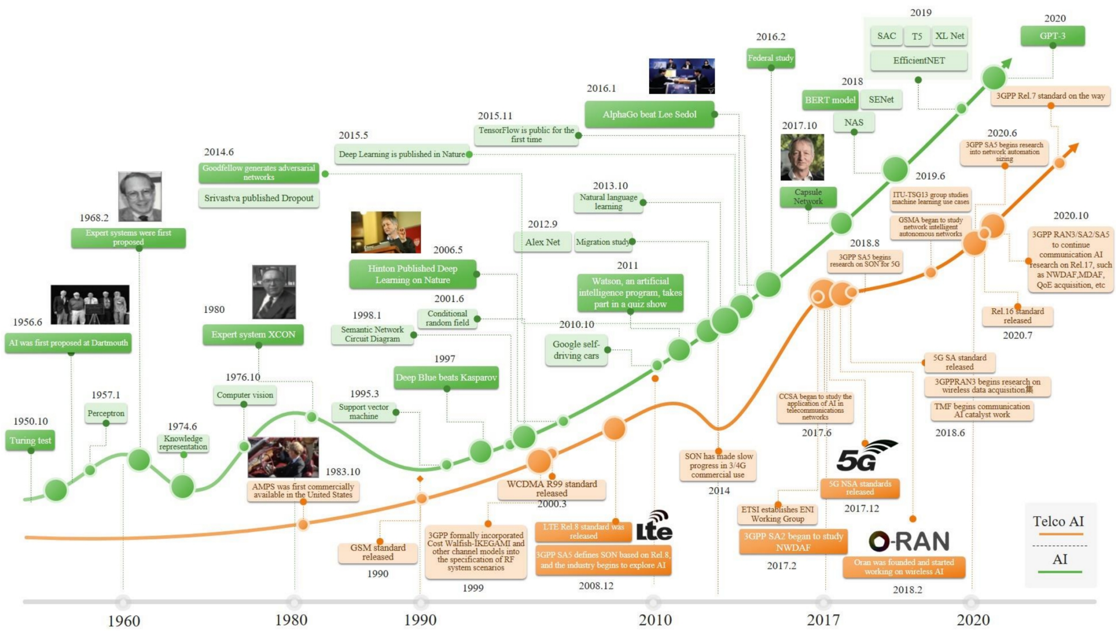

Figure 2.1: Evolution of Telecommunication and AI-ML

Historical Development of Telecommunication: The evolution of telecommunication technology spans over four decades, marking a remarkable transformation from basic analog voice systems to today's sophisticated digital networks. Beginning with the commercialization of analog voice communication in 1983, the industry progressed through multiple generations - from the digital voice capabilities of 2G in

1991 to the mobile internet solutions of 3G in 2001, followed by the all-IP broadband connectivity of 4G, and finally to the current 5G technology. This journey represents a shift from simple voice-only services to comprehensive digital ecosystems that enable diverse applications across industries. In the development of telecommunication technology from 2G to 5G [13], the industrial field basically evolves along the main line with 3GPP as the fact technology standard and is supplemented by other technology standards such as European telecommunications standards institute (ETSI), ITU [22], open RAN alliance (O-RAN)[66], etc. as the sideline. Since 2008, 3GPP has gradually introduced the AI concept to the technology standards of the telecommunication network, with self-organizing networks (SON)[25] technology as a significant mark.

Historical Development of AI-ML: The journey of artificial intelligence began at the Dartmouth Conference in 1956, where the term "AI" was first coined alongside the introduction of Computational Learning Theory. After initial progress in bionics and expert systems during the mid-1990s, AI faced a development plateau until IBM's Deep Blue achieved its landmark success in 1997. The field experienced a renaissance in the early 21st century, transitioning from mere perception to cognitive capabilities. Key breakthroughs included AlexNet's revolutionary convolutional network in 2012, significant advances in natural language processing through RNN and word2vec in 2013, and the emergence of GANs in 2014. Recent developments have been particularly dramatic, from Google's AlphaGo triumph to the release of powerful language models like BERT and GPT-3. The field has also evolved to address data privacy concerns, notably through the introduction of Federated Learning in 2017, culminating in the IEEE P3652.1 standard for industrial applications by 2020.

Historical Development of Telecommunications AI-ML: The integration of AI into telecommunications has evolved from simple beginnings to sophisticated applications. Early telecommunication systems relied primarily on data-driven models for network planning, starting with the Okumura model in 1968 and the Hata model in 1980. A significant shift occurred in 2008 when 3GPP introduced Self-Organizing Networks (SON), marking the formal entry of AI concepts into telecommunication standards. The field gained momentum from 2017 onward, with major developments including 3GPP's Network Data Analytics Function (NWDAF)[53] for 5G core networks and ETSI's Experiential Networked Intelligence group. The establishment of the O-RAN Alliance in 2018 marked a crucial turning point, leading the development of open, intelligent radio access networks. Today, the O-RAN Alliance continues to drive innovation through its RAN Intelligent Controllers (RIC) and AI/ML applications for network optimization, having expanded to over 300 members globally and playing a pivotal role in shaping the future of telecommunications AI. The industry has advanced rapidly, incorporating sophisticated AI applications across network management, from core network functions to radio access optimization, culminating in the integration of Federated Learning into 5G standards and the continuous evolution of AI-driven network automation systems.

The significance of this evolution cannot be overstated. As networks become more complex and user demands more sophisticated, the role of AI/ML technologies becomes increasingly critical. Understanding these technologies and their implementation is essential for anyone involved in modern telecommunications, from network engineers to system architects and policy makers.

2.1 Cross-Domain Applications in Forecasting: Insights for Telecommunications

The examination of forecasting methodologies across different domains offers valuable perspectives for telecommunications forecasting policy development. While these domains differ in their specific challenges, their methodological advances and lessons learned can inform telecommunications forecasting approaches.

In the financial sector, Pai and Lin [7] developed a hybrid methodology combining ARIMA models with Support Vector Machines (SVM) for stock price forecasting. Their research demonstrated that stock prices, characterized by both linear trends and nonlinear market behaviors, could be more accurately predicted using hybrid models rather than single-method approaches. While stock market dynamics differ from telecommunications traffic patterns, the principle of combining linear and nonlinear modeling techniques remains relevant. Telecommunications traffic similarly exhibits both predictable patterns (like daily and weekly cycles) and nonlinear behaviors (such as sudden spikes during events or emergencies), suggesting potential benefits from such hybrid approaches.

Goodwin [39] presents comprehensive guidelines for sales forecasting, focusing on practical implementation and organizational integration. Despite sales forecasting's distinct nature from telecommunications, several key principles transfer effectively. Sales forecasting's emphasis on hierarchical data structures parallels telecommunications' need to forecast at various network levels, from individual cell towers to regional networks. Goodwin's framework for forecast evaluation and adjustment processes provides valuable insights for telecommunications, particularly in developing systematic approaches to forecast verification and correction procedures across different network scales.

The solar energy domain, as examined by Barhmi, Heynen, Golroodbari, *et al.* [65], presents interesting parallels to telecommunications forecasting. Their analysis of solar forecasting techniques emphasizes the critical role of temporal granularity in forecast accuracy. Solar generation, like telecommunications traffic, requires predictions across multiple time horizons, from immediate short-term to long-range planning. The challenges they identify in handling weather variability mirror telecommunications' challenges with event-driven traffic spikes. Their findings regarding the integration of physical models with AI-driven approaches suggest similar potential for combining network physics models with AI techniques in telecommunications forecasting.

These cross-domain insights suggest several key considerations for telecommunications forecasting policy development. First, the success of hybrid models in stock price forecasting indicates potential benefits from combining traditional time series methods with machine learning approaches in telecommunications. Second, the structured approach to forecast implementation and organizational integration from sales forecasting provides a template for developing comprehensive telecommunications forecasting policies. Third, the multi-temporal nature of solar forecasting and its solutions offers valuable lessons for handling telecommunications' varying prediction horizons.

The synthesis of these diverse forecasting applications indicates that telecommunications forecasting policies should incorporate structured approaches to method selection and implementation, while maintaining domain-specific considerations. The integration of forecasting methods should account for telecommunications' unique characteristics, including network hierarchies, varying time scales, and the interplay between regular patterns and irregular events. Effective policies must address data preparation, method selection, forecast validation, and integration with existing network management systems, all while considering the specific requirements of telecommunications operations.

This cross-domain analysis provides a foundation for developing telecommunications forecasting policies that leverage proven approaches from other fields while maintaining focus on the unique aspects of telecommunications networks. The resulting framework should enable robust forecasting capabilities that support both operational efficiency and strategic planning in telecommunications networks.

2.2 Integration of Traditional and Modern Forecasting Methods

The telecommunications industry has undergone significant transformation in recent years, particularly with the widespread deployment of 5G networks and proliferation of mobile devices. As emphasized by Yu, Li, Jin, *et al.* [55], network operators now face unprecedented challenges in managing massive data growth while dealing with increasingly complex and dynamic traffic patterns. The accuracy of forecasting has become crucial for ensuring quality of service, reducing operational costs, and optimizing resource allocation in modern telecommunications networks.

Telecommunication forecasting encompasses many areas, from network traffic prediction to resource optimization and customer behavior analysis. Research by Zhang, Patras, and Haddadi [50] demonstrates that traditional statistical approaches, while foundational, often struggle to capture the complex nonlinear patterns present in modern telecommunications data. Their findings indicate that deep learning techniques have emerged as powerful tools for handling these challenges, particularly in cellular traffic prediction where both spatial and temporal dependencies must be considered.

The evolution of forecasting methodologies in telecommunications reflects the industry's growing complexity. Armstrong and Green [38] highlight the importance of developing standardized approaches to data collection, processing, and analysis. Their work emphasizes that successful forecasting requires not just sophisticated algorithms, but also robust frameworks for data quality management and performance evaluation. This includes establishing consistent validation methods, implementing standardized metrics for accuracy assessment, and developing clear guidelines for method selection based on specific application requirements.

Deep learning-based models have demonstrated particularly remarkable improvements in cellular traffic prediction, showcasing their ability to capture complex temporal and spatial dependencies in network data. Do, Doan, Nguyen, *et al.* [52] presented compelling evidence that neural networks have become the predominant method for traffic prediction, specifically due to their capability to capture non-linear patterns and complex relationships in network traffic data, offering superior performance compared to traditional methods.

While modern approaches dominate current research, traditional statistical approaches and machine learning methods maintain important roles in telecommunications forecasting. Ferreira, Ravazzi, Dabbene, *et al.* [61] conducted an extensive comparison of various forecasting techniques, revealing that while modern deep learning methods often achieve superior accuracy, traditional approaches retain relevance due to their interpretability and lower computational requirements. Their analysis demonstrates that statistical models and classical machine learning approaches remain valuable, particularly in scenarios where explainability is crucial.

The integration of multiple methodologies has gained significant traction in recent years. Research by Wu, Du, Zhang, *et al.* [64] demonstrates that hybrid approaches combining different techniques have shown promising results in cellular traffic prediction. These combined methods leverage the strengths of both traditional statistical models and advanced deep learning architectures, offering improved prediction accuracy while maintaining practical applicability.

Recent developments in the field show an increasing focus on real-time processing capabilities and handling large-scale data. The advancement of deep learning architectures has enabled better management of multi-dimensional features and complex pattern recognition, particularly crucial in modern telecommunications networks. Yang [49] emphasizes that the selection of forecasting methods increasingly depends on specific application requirements, including prediction accuracy, computational efficiency, and model inter-pretability.

This evolution in forecasting approaches reflects the growing complexity of telecommunications systems and their data. While deep learning methods, particularly neural networks, dominate contemporary research and applications, the field benefits from a diverse range of methodologies. Each approach serves specific use cases and requirements in the telecommunications industry, contributing to a comprehensive ecosystem of forecasting solutions.

2.3 Data Preprocessing and Variation Analysis

Data preprocessing and variation analysis play crucial roles in developing accurate and reliable forecasting models in telecommunications. These foundational aspects significantly influence model performance and reliability in practical applications, requiring careful consideration and systematic approaches.

Traditional data splitting approaches have been critically examined in recent telecommunications research. Yu, Li, Jin, *et al.* [55] conducted comprehensive research on fair train-test splitting methodologies, focusing particularly on spatial data characteristics in machine learning applications. Their investigation revealed that conventional random splitting approaches often prove suboptimal when handling spatially correlated data, such as telecommunications network information. Their work demonstrated the significant impact of spatial autocorrelation on model performance and introduced methods for mitigating bias through proper data partitioning strategies. Building on these data splitting considerations, Zhang, Patras, and Haddadi [50] provided a critical examination of current practices, highlighting common pitfalls such as ignored temporal dependencies and data leakage issues. Their research established best practices for time-aware splitting strategies and domain-specific considerations, emphasizing the crucial relationship between splitting strategies and model accuracy in real-world applications.

In the realm of data variation analysis, Armstrong and Green [38] contributed significantly by examining various tests for detecting seasonality in time series data. Their research established comprehensive frameworks for pattern identification and comparison of different testing approaches, particularly relevant for telecommunications data where seasonal patterns significantly influence network traffic and usage patterns. Do, Doan, Nguyen, *et al.* [52] advanced the understanding of seasonality by investigating dynamic patterns in time series data. Their research revealed complex seasonal characteristics including time-varying patterns, multiple seasonal frequencies, and interactions between different seasonal components. Their work introduced adaptive seasonal detection methods and robust approaches for handling changing patterns in telecommunications data.

Recent developments by Wu, Du, Zhang, *et al.* [64] introduced an innovative encoder-decoder system for handling multivariate time series data. Their framework advanced multivariate pattern recognition and real-time processing capabilities, demonstrating improved accuracy in anomaly detection while reducing false positive rates in complex data patterns.
The field continues to evolve with emerging trends in context-aware splitting, advanced validation strategies, and comprehensive data quality assurance measures. Yang [49] emphasizes the importance of automated preprocessing pipelines, enhanced domain knowledge integration, and sophisticated validation techniques for time series data. These developments reflect the growing understanding of data characteristics and their critical impact on model performance in telecommunications applications.

This evolution in data preprocessing and variation analysis demonstrates that these aspects are not merely preliminary steps but crucial components that significantly influence the success of forecasting models in telecommunications. The progression from simple techniques to sophisticated approaches reflects the increasing complexity of telecommunications data and the need for more nuanced handling methods. The integration of advanced preprocessing techniques with domain-specific knowledge has become essential for developing robust and reliable forecasting models.

2.4 Approaches for Improving Forecasting Accuracy

The accuracy of forecasting models in telecommunications heavily depends on systematic optimization techniques and parameter tuning methodologies. Recent research has revealed significant advances in enhancing prediction accuracy through sophisticated optimization approaches, moving beyond traditional manual tuning methods to more systematic and automated solutions.

Yu, Li, Jin, *et al.* [55] conducted a comprehensive review of hyperparameter optimization algorithms, revealing a critical insight: traditional manual tuning approaches frequently fail to achieve optimal results in complex telecommunications applications. Their research demonstrates that systematic parameter selection plays a pivotal role in model performance, introducing a spectrum of optimization strategies ranging from basic grid search methods to sophisticated automated approaches. This work established fundamental principles for systematic optimization in telecommunications forecasting.

Building on these foundations, Zhang, Patras, and Haddadi [50] introduced a structured approach to machine learning model optimization specifically tailored for telecommunications applications. Their research established that systematic parameter tuning could significantly improve prediction accuracy across various domains within telecommunications. Their framework provides a comprehensive methodology addressing four critical aspects: parameter space definition, search strategy selection, cross-validation approaches, and performance metric evaluation. This integrated approach creates a robust foundation for model optimization in practical applications.

Significant advancements in search methodologies came from Armstrong and Green [38], who conducted extensive investigations into random search techniques for hyperparameter optimization. Their research revealed a surprising finding: random search methods could achieve comparable or superior results to traditional grid search approaches while demanding substantially fewer computational resources. This work demonstrated enhanced efficiency in exploring large parameter spaces and improved scalability for high-dimensional optimization problems common in telecommunications forecasting.

A major breakthrough in optimization efficiency emerged from research by Do, Doan, Nguyen, *et al.* [52], who developed a comprehensive system for massively parallel hyperparameter tuning. Their research introduced scalable architecture for distributed optimization, incorporating efficient resource allocation methods and sophisticated parallel execution techniques. This system demonstrated remarkable improvements in optimization efficiency, particularly beneficial for large-scale telecommunications applications where computational resources often constrain optimization efforts.

The field continues to evolve with emerging trends in optimization approaches, as documented by Wu, Du, Zhang, *et al.* [64]. Current research indicates movement in three primary directions: the integration of automated machine learning techniques, development of multi-objective optimization strategies, and creation of adaptive optimization systems. These advanced techniques reflect the growing need for intelligent optimization systems that can adapt to specific problem characteristics while effectively managing computational constraints.

This evolution in optimization approaches underscores the critical importance of proper model tuning in achieving reliable predictions in telecommunications forecasting. The progression from basic grid search methods to sophisticated parallel optimization systems, as noted by Yang [49], demonstrates the field's response to increasingly complex telecommunications forecasting challenges. These advancements provide a foundation for more efficient and accurate forecasting systems, capable of handling the demanding requirements of modern telecommunications applications while maintaining computational efficiency.

2.5 Model Selection and Use of Fused Methods

The evolution of forecasting in telecommunications has led to increasing interest in hybrid approaches that combine multiple methodologies. Yu, Li, Jin, *et al.* [55] conducted pioneering research on combining linear and non-linear time series models, demonstrating that combined forecasting methods consistently outperform individual approaches. Their research established that model combination strategies can effectively compensate for individual model weaknesses, resulting in more robust predictions in complex applications.

Developing on this foundation, Zhang, Patras, and Haddadi [50] made significant contributions through the development of a hybrid methodology combining ARIMA and neural network models. Their research revealed a crucial insight: while ARIMA models excel at capturing linear relationships, neural networks effectively model nonlinear patterns. By decomposing time series into linear and nonlinear components, their hybrid approach enabled each model type to focus on its strengths, leading to superior overall performance. The study demonstrated improved accuracy across various time horizons, establishing the effectiveness of this combined approach in telecommunications forecasting applications.

Recent developments by Armstrong and Green [38] have further advanced the field through sophisticated approaches to long-term multivariate time series forecasting. Their research introduced innovative series decomposition techniques that separate complex patterns into manageable components, while integrating convolutional neural networks for enhanced feature extraction. Their multi-component architecture enables parallel processing of different time series aspects and implements adaptive weighting of component contributions, resulting in significant improvements in long-term prediction accuracy for telecommunications networks.

The integration of multiple modeling approaches has been further refined through research by Do, Doan, Nguyen, *et al.* [52], who developed adaptive weighting schemes for model combinations. Their work demonstrated that dynamic adjustment of model weights based on recent performance can significantly enhance prediction accuracy, particularly in telecommunications applications where data patterns exhibit temporal variations. This adaptive approach provides a more robust framework for handling the evolving nature of network traffic and usage patterns.

Advanced ensemble techniques have emerged as a promising direction, as documented by Wu, Du, Zhang, *et al.* [64]. Their research established frameworks for hierarchical model integration, where different techniques are combined at multiple levels to capture various aspects of telecommunications data. These developments reflect the growing sophistication of forecasting requirements in telecommunications applications, where simple model combinations no longer suffice for achieving desired accuracy levels.

The field continues to evolve with emerging trends in combined methods, as noted by Yang [49]. Contemporary research focuses on developing adaptive combination strategies that dynamically adjust weights based on recent performance, multi-level integration approaches that combine different modeling techniques hierarchically, and advanced ensemble learning extensions. These developments reflect the growing sophistication of forecasting requirements in telecommunications applications.

The progression from simple model combinations to sophisticated multi-component architectures demonstrates the field's response to increasingly complex forecasting challenges. This evolution has led to more nuanced solutions that can better handle the multi-faceted nature of telecommunications data while maintaining practical applicability and computational efficiency. The success of these combined approaches suggests future developments will continue to focus on integrating multiple methodologies while enhancing their inter-pretability and real-time adaptation capabilities.

The adoption of combined methods has revolutionized telecommunications forecasting by enabling more comprehensive and accurate predictions. These integrated approaches have demonstrated superior performance compared to traditional single-model methods, particularly in handling the complex, multi-dimensional nature of modern telecommunications data. The continued development of sophisticated combination strategies promises further improvements in forecasting accuracy and reliability.

Chapter 3

Mobile Network and KPIs

This chapter provides a comprehensive exploration of mobile network fundamentals and their performance measurement systems. The content unfolds across several key sections, starting with the foundational architecture of mobile networks. We explore how different network elements interconnect and work together to provide seamless communication services to users.

Following the architectural overview, we examine telecom sites in detail. This section covers the physical infrastructure that powers our mobile networks, including base stations, antenna systems, and supporting equipment. Understanding these components helps readers grasp how theoretical network concepts translate into real-world implementations.

The chapter then presents two distinct practical scenarios that demonstrate how user behavior affects network quality. These real-world examples illustrate common challenges network operators face and their solutions. Through these scenarios, readers gain practical insights into how network performance varies under different conditions and usage patterns.

The final section delves into Key Performance Indicators (KPIs)[44][45], the essential metrics used to measure and monitor network performance. We provide detailed descriptions of various KPIs, explaining how they are calculated, what they measure, and why they matter for network optimization. This section helps readers understand how network operators use data to maintain service quality and identify areas for improvement.

3.1 Mobile Network Basics

Mobile networks form the backbone of modern wireless communications, representing a complex yet elegant system that has revolutionized how we connect and communicate. These networks operate on a cellular principle, where geographical areas are divided into smaller sections called cells, each served by at least one fixed-location transceiver known as a base station.

The fundamental concept behind mobile networks is relatively straightforward: they

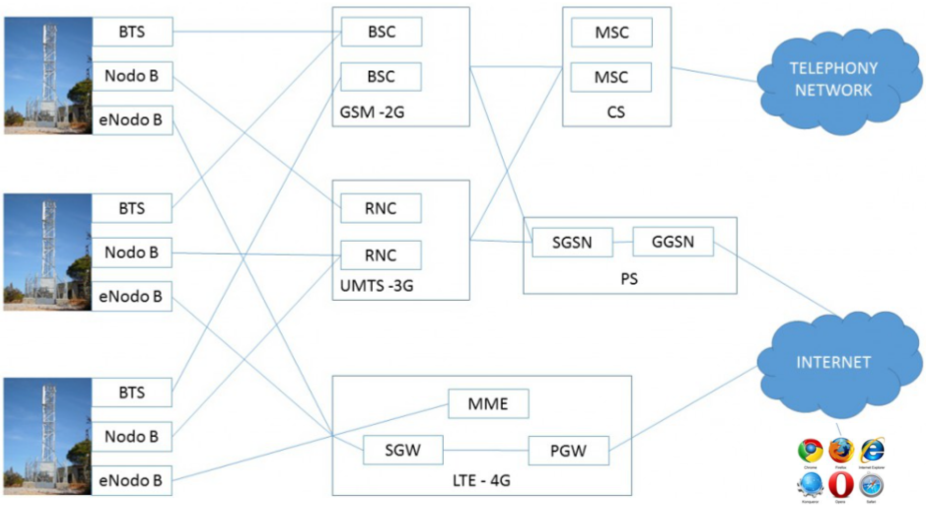

Figure 3.1: 2G, 3G & 4G Mobile Network

provide wireless connectivity by transmitting radio signals between fixed ground-based stations and mobile devices. However, the technical implementation is remarkably sophisticated, involving multiple layers of technology working in harmony to deliver reliable service. Each generation of mobile technology, from 2G through to modern 5G networks, has built upon this basic principle while introducing increasingly advanced capabilities.

A mobile network's architecture [30] can be broadly divided into two main components: the Radio Access Network (RAN) and the Core Network. The RAN handles all radio-related functions, managing the wireless communication between mobile devices and the network. This includes tasks such as radio resource management, compression of voice data, and ensuring secure data transmission. The Core Network, meanwhile, serves as the central part of the system, managing all the permanent data of mobile subscribers and establishing connections to external networks.

What makes mobile networks particularly fascinating is their ability to maintain continuous service while users move between cells. This handover process, happening seamlessly in the background, requires precise coordination between network elements and represents one of the most significant achievements in telecommunications engineering. The network must constantly track device locations, manage radio resources, and coordinate between cells to ensure uninterrupted service.

At the heart of this infrastructure are cell towers, alternatively referred to as telecoms sites or phone masts. These structures house electrical communications equipment and antennae, enabling the surrounding region to use wireless communication devices such as mobile phones and radios. Some sites also have powerful broadcasting towers that broadcast television signals. They play a major role in connecting the network as a whole, ensuring that data is delivered uninterrupted and with minimal delay.

Figure 3.2: A Green Field Site

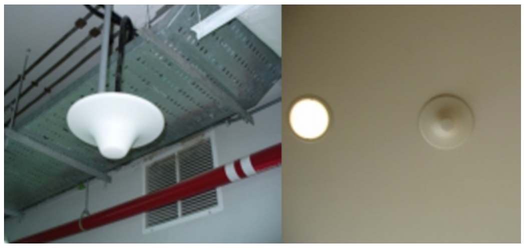

Figure 3.3: IBS ANtenna

There are several distinct types of telecoms sites, each designed to serve specific environments and purposes. Greenfield sites, IBS[60], rooftops, and occasionally streetworks make up the primary categories. Rooftops are typically found in built-up areas, where antennas broadcast mobile signals and act as "hops" to other hubs. A greenfield telecoms site, illustrated in Figure 3.7, is a tall tower built in rural or remote areas, or on industrial sites, where it's not part of existing infrastructure. IBS, or In-Building Solution, provides mobile coverage in indoor spaces where normal mobile networks are inadequate. These solutions are particularly vital in large indoor spaces like malls, hospitals, office complexes, and airports, with an example shown in Figure 3.8.

3.2 Mobile Network Architecture: From 2G to 4G

3.2.1 From Phone Calls in 2G to Mobile Data in 3G

The transition from 2G to 3G was primarily motivated by the need to introduce mobile internet and additional capabilities to the existing 2G networks. The Global System for Mobile Communications (GSM), also known as 2G, was developed in the 1980s with the primary goal of providing voice calls to mobile users [11]. GSM adopted well-established circuit-switched digital communication solutions, ensuring compatibility between fixed and mobile networks [3].

From a Radio Access Network (RAN) perspective, referred to as the Base Station Subsystem (BSS) in GSM terminology, 2G networks rely on the Base Station Controller (BSC). The BSC handles radio resource management, handover, power management, and signaling for a set of Base Stations (BSs), also known as the Base Transceiver Subsystem (BTS). In the Core Network (CN), referred to as the Network Subsystem (NSS), the Mobile Switching Centre (MSC) manages multiple BSCs and configures user traffic via the Home Location Register (HLR), a database that stores subscription information. The Gateway Mobile Switching Centre (GMSC) serves as the edge node, interconnecting the GSM network with external Public Switched Telephone Networks (PSTN) and Integrated Services Digital Networks (ISDN). In 2G networks, both user traffic (U-plane) and control traffic (C-plane) are managed

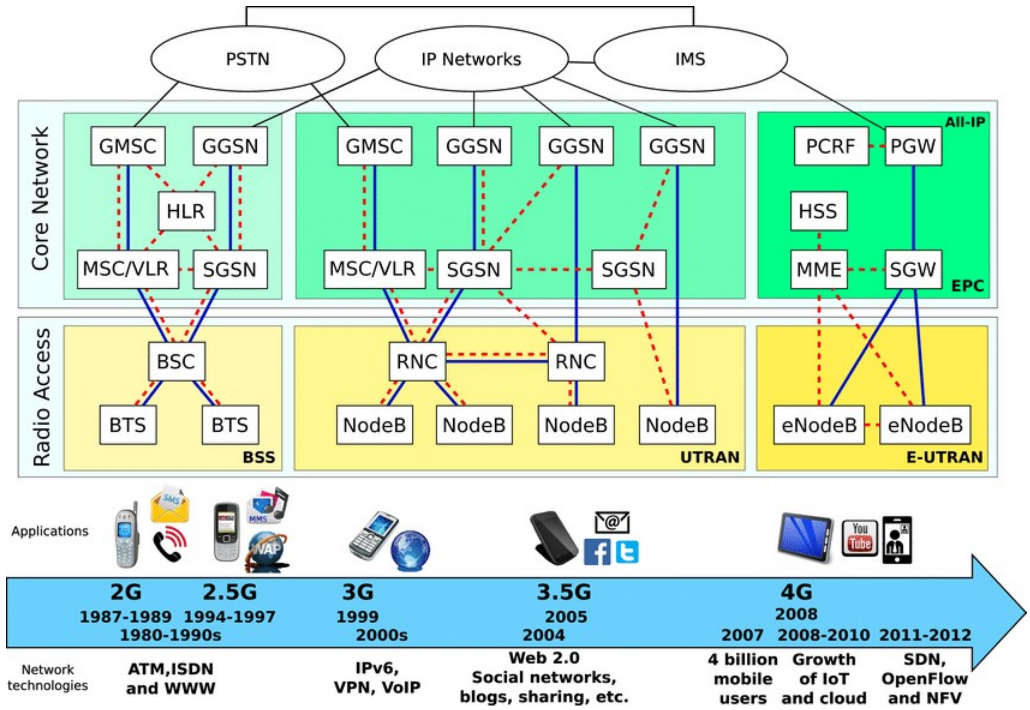

Figure 3.4: Mobile Network Architecture

by all network entities. In the 1990s, the General Packet Radio Service (GPRS), also referred to as 2.5G, introduced data connectivity over mobile networks through the Wireless Application Protocol (WAP)[4]. The primary architectural enhancement of GPRS compared to GSM was in the CN, with the introduction of packet-switched communications using the Asynchronous Transfer Mode (ATM) protocol. Architecturally, GPRS introduced the Serving GPRS Support Node (SGSN), which provides MSC-like functionalities for packet-switched traffic, and the Gateway GPRS Support Node (GGSN) to connect with external packet-switched networks [2].

In the 1990s, market demand for higher data rates for web browsing via HTTP led to the development of 3G mobile networks. The Universal Mobile Telecommunications Service (UMTS), as defined by the 3rd Generation Partnership Project (3GPP) Release 99[12], addressed the limitations of 2.5G[10] by utilizing Wideband Code Division Multiple Access (WCDMA) to optimize radio resource utilization **ref6**. The Universal Terrestrial Radio Access Network (UTRAN) introduced enhanced functionalities in the eNodeB, such as rate adaptation, closed-loop power control, and load management at the Radio Network Controller (RNC). While the CN maintained both circuit- and packet-switched domains, advancements in 3.5G (HSPA) and later releases streamlined the architecture, enabling features like direct tunnels to bypass the SGSN for user-plane traffic [18].

3.2.2 The 4G Architecture

The evolution from 3G to 4G was driven by the need for high-speed data connectivity to support real-time internet applications such as voice over IP (VoIP), video streaming, and video calls[27]. The industry adopted the 3GPP Release 8 standard, which introduced the Evolved-UTRAN (E-UTRAN) and the Evolved Packet Core

(EPC), collectively known as 4G or Long Term Evolution (LTE). This new architecture utilized Orthogonal Frequency Division Multiplexing (OFDM) to improve data rates and radio resource management [17].

One of the most significant changes in 4G was the shift to a flat, all-IP network architecture, where both voice and data traffic are handled by a single CN. This shift leveraged advances in IP-based Quality of Service (QoS)[5] management, replacing ATM-based solutions for data traffic and circuit-switched networks for voice calls. The resulting architecture enabled efficient management of heterogeneous traffic with varying QoS requirements, including packet loss, delay tolerance, and prioritization.

The 4G architecture further enhanced the control/user-plane (C/U-plane) split introduced in 3.5G Sesia, Toufik, and Baker [15]. The Evolved NodeB (eNodeB) acts as the sole entity in the E-UTRAN, anchoring both planes. In the EPC, the Serving Gateway (SGW) and the Packet Data Network Gateway (PGW) manage the user plane. The SGW serves as the termination point of the packet data interface to the E-UTRAN and acts as a local mobility anchor during handovers. The PGW terminates the interface with external networks and supports policy enforcement, packet filtering (e.g., deep packet inspection), and charging mechanisms through the Policy and Charging Rules Function (PCRF).

On the control plane, the Mobility Management Entity (MME) handles security procedures such as authentication, signaling for packet data context setup, and location management through the tracking area update process. The MME relies on the Home Subscriber Server (HSS) for subscription information retrieval. While 4G architecture simplifies management and scalability compared to its predecessors, it also presents limitations in terms of flexibility [24].

3.3 Description of a Telecom Site

Site refers in telecom network to the actual structure (towers). Housing the equipment required to power and operate cells. Each cell site hosts one or more base stations that emit radio signals, creating a specific cell, an area where users can connect to the network. Cell sites house transmitters, receivers, antennas, power units, and other related electronics for signal amplification, routing, and network connectivity. Cells is Unlike a physical structure, a cell is a defined zone within the network coverage, often represented as a hexagon or circle on a map. Within a cell, users with compatible devices can connect to the network base station for calls, data transfers, and other services.
As described in the Figure 3.5, a cellular network is composed of several interconnected components that work together to provide wireless communication services. The key terms used in the image are:

Cell: A cell[62] is the smallest unit of coverage in a cellular network. It is a geographical area served by a single sector of a site. The image illustrates how multiple cells can overlap to provide continuous coverage within a Thana. As per the figure,

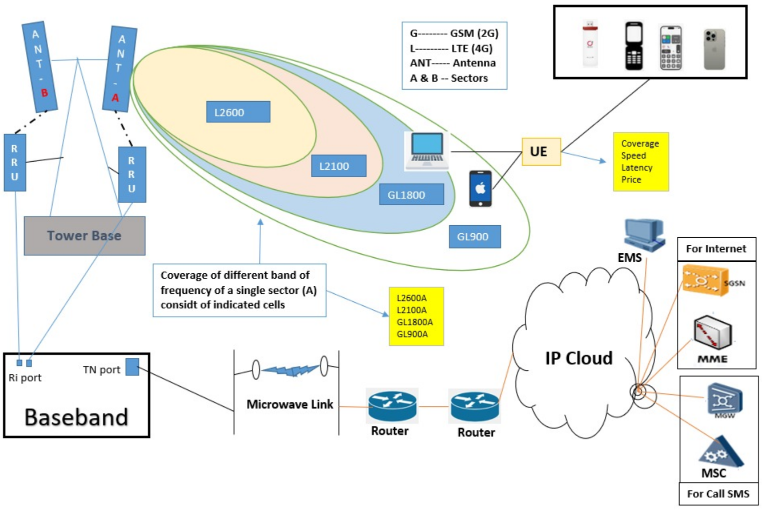

Figure 3.5: Site diagram

each cell consist of 1 LTE 2600 band cell, 1 LTE 2100 Band cell, 1 combined (GSM & LTE) cell of each 1800 and 900 band.

Sector: A sector[14] is a portion of a site's coverage area. It is defined by the direction of the antenna beams and the geographical boundaries of the coverage. The image shows that a site can have multiple sectors, each covering a different area within the Thana. Each sector can have multiple cells of different band or same band with different services. As per the figure, Sector A is consist of 4 different band (2600, 2100. 1800 & 900) and 2 different services (GSM & LTE).

Site: A site[14] is a physical location where cellular equipment is installed. It typically includes a tower, antennas, and other necessary infrastructure to provide wireless coverage to a specific area. The image depicts multiple sites within a Thana, each serving a portion of the population. A site is consist of 3 sectors usually, but sometime a site can have more or less than 3 sectors. In this image 3 sectors are considered under a site.

Thana: A Thana (now known as upazila[67] or subdistrict) is an administrative region that acts as a division within a district. Each district is subdivided into several upazilas, which are responsible for local governance and administration. In the context of cellular network, a thana is consist of few sites and is the minimum area that is considered for cellular network KPI monitoring.

3.4 Flow of Service and Impact on KPI

The service flow in modern telecommunications networks follows two main paths: voice and data. For voice services, the call originates from the User Equipment (UE), travels through the Radio Antenna interface to the Baseband Unit for processing. The signal then moves through the Microwave transport layer and Router before reaching the IP Cloud. Finally, it connects to the MSC (Mobile Switching

Center) in the core network for voice call handling.

Data services follow a similar physical path but connect to different core elements. Data traffic from the UE passes through the same radio and transport infrastructure but is directed to the SGSN (Serving GPRS Support Node) for data session management. For 4G services, the traffic is handled by the MME (Mobility Management Entity), while 5G services are managed by the AMF (Access and Mobility Management Function). This architecture ensures efficient handling of both voice and data services while maintaining service quality and network reliability.

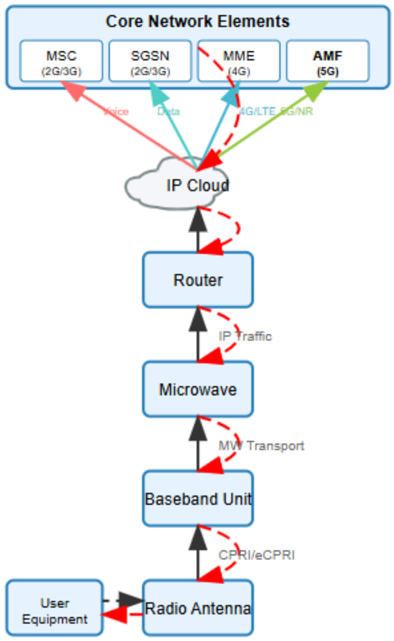

Figure 3.6: Flow of Voice and Data Service

Transport capacity through microwave links plays a vital role in determining service quality in telecommunications networks. When bandwidth limitations occur in these links, they can trigger a cascade of performance issues. Link saturation commonly results in increased transmission delays, reduced data throughput, and elevated network latency levels. These performance degradations become particularly noticeable in applications that demand real-time responsiveness, such as video conferencing systems, online gaming platforms, and interactive streaming services. These applications require consistent, low-latency connections to maintain optimal user experience, making them especially vulnerable to any constraints in the microwave transport layer's capacity.

$$\text{\textit{User Experience}} \propto \text{\textit{Microwave Link Capacity}} \tag{3.1}$$

Impact on Cell Traffic In cellular networks, increased traffic within a single cell can create significant ripple effects across the network through inter-cell interference. When a base station responds to higher traffic demands by boosting its transmission power to maintain service quality, this elevated power level spills over into neighboring cells, creating interference patterns. This interference cascade manifests in multiple performance issues: degraded signal quality across affected cells, higher rates of dropped calls, noticeable reductions in data transmission speeds, and increased network latency. These combined effects can significantly impact the overall network performance and user experience across multiple adjacent cells, highlighting the interconnected nature of cellular network operations.

3.5 Practical Scenario

To understand better, we have shared 2 different scenario where user experience changed based on network capacity.

3.5.1 Practical Scenario 1: Impact of User Density on Network Performance

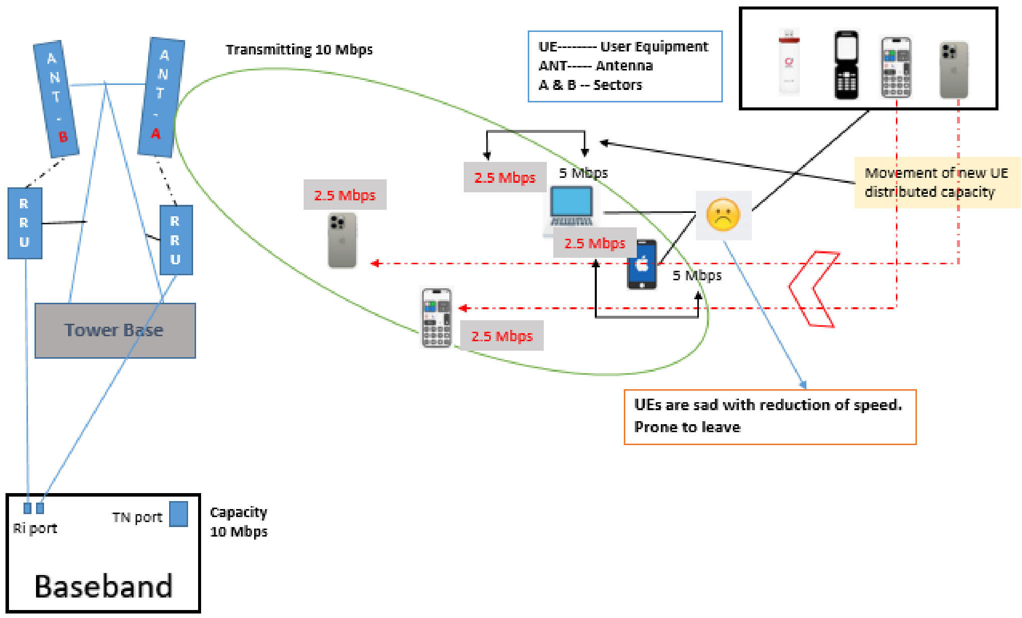

Figure 3.7: Impact of Bandwidth Shortage on Telecom User

Initial State:

Two UEs are initially connected to the base station (BS) with a total transmission capacity of 10 Mbps. Each UE receives an initial throughput of 5 Mbps.

Introduction of New UEs:

The network sees an increase in user density as two additional UEs join the network. Despite the BS capacity remaining at 10 Mbps, the available bandwidth per UE decreases to 2.5 Mbps.

Impact on Key Performance Indicators (KPIs):

- **User Throughput:** A significant decrease in user throughput is observed as the number of UEs increases.
- **Latency:** Increased contention for resources leads to elevated latency levels.
- **Packet Loss:** Network congestion results in higher packet loss rates.

Correlation at Cell/Site Level:

- **User Density vs. User Throughput:** As shown in Figure **??**, there is a strong negative correlation between user density and user throughput. An increase in user density causes a significant drop in user throughput.
- **User Density vs. Latency and Packet Loss:** There is a strong positive correlation between user density and both latency and packet loss. As user density increases, both latency and packet loss rates rise significantly.

3.5.2 Practical Scenario 2: Impact of User Density on Network Performance

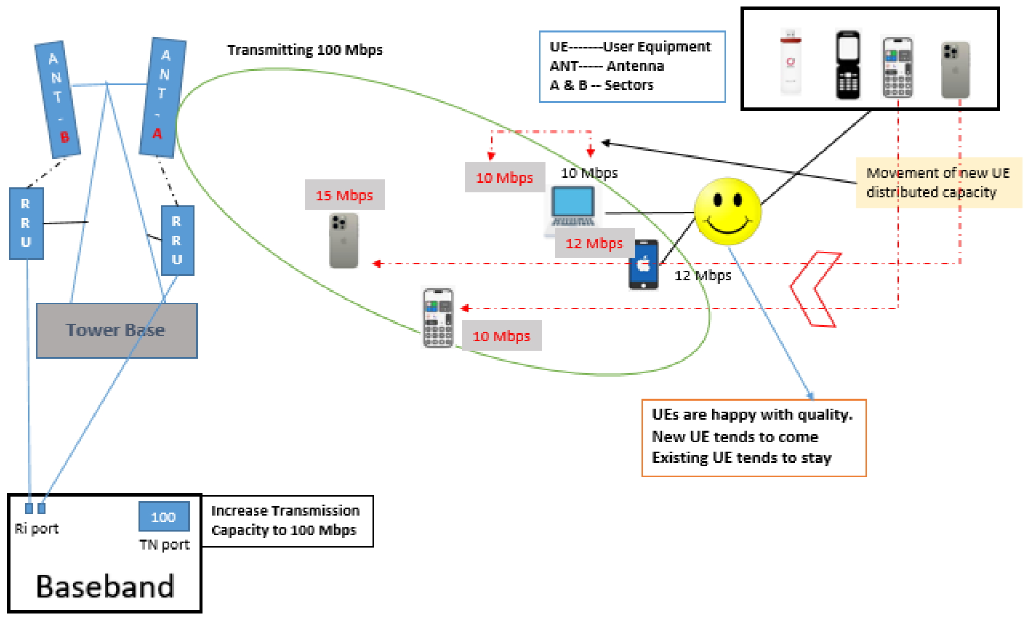

Figure 3.8: Enhanced Bandwidth and Its Positive Effects on Telecom User

Initial State

Two UEs are connected to the BS with a total transmission capacity of 10 Mbps. Each UE receives an initial throughput of 5 Mbps.

Capacity Enhancement

The BS transmission capacity is increased to 100 Mbps.

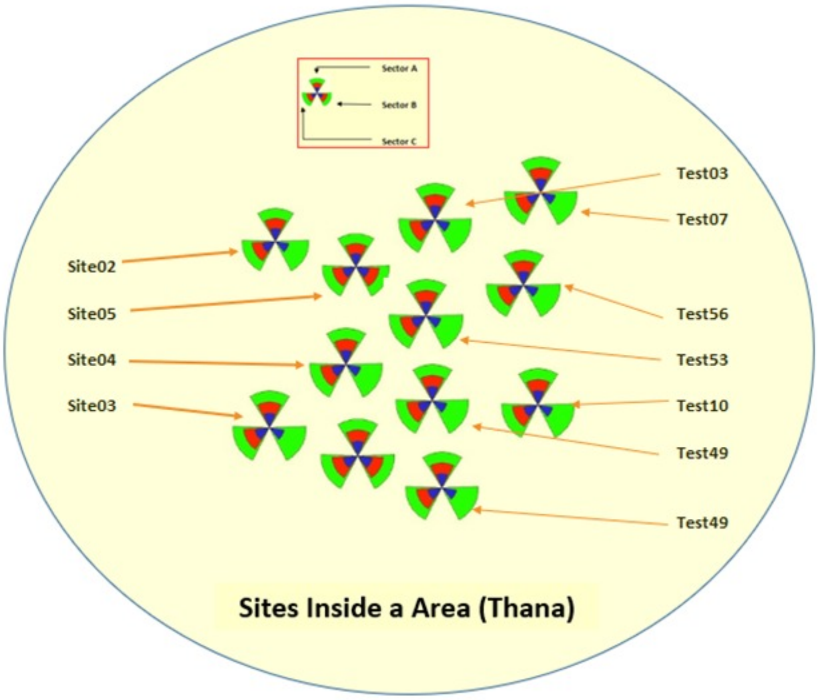

Figure 3.9: Area (Thana) wise site coverage

Introduction of New UEs

The network sees an increase in user count as two additional UEs join the network and the Site capacity increased to 100 Mbps, the available bandwidth per UE decreases to 25 Mbps.

Impact on Key Performance Indicators (KPIs)

- **User Throughput:** A significant increase in user throughput is observed
- **Latency:** Reduced network congestion leads to significantly lower latency.
- **Packet Loss:** The likelihood of packet loss decreases significantly

Correlation at Cell/Site Level

- **User Density vs. User Throughput:** As shown in Figure **??**, At the cell/site level, there is a strong positive correlation between Transmission Capacity and User Throughput. Increased capacity leads to higher throughput.
- **User Density vs. Latency and Packet Loss:** There is a strong negative correlation between Transmission Capacity and both Latency and Packet Loss. Increased capacity leads to lower latency and reduced packet loss..

3.5.3 Impact at Area Level

As the area under consideration increases, encompassing a larger number of cells and UEs, the correlation between User Density and User Throughput weakens due to several factors:

- Network operators employ load balancing techniques to distribute traffic across multiple cells, thereby mitigating congestion in individual cells.
- In dense urban environments, overlapping cells allow UEs to connect to cells with better coverage and less congestion, improving overall throughput.
- In larger areas, macro diversity effects come into play, where UEs experience varying propagation conditions and interference levels, leading to diverse throughput levels even within the same area.

3.5.4 Key Takeaways from Practical Scenario

Cell/Site Level: At the cell or site level, strong correlations are observed between KPIs such as User Density, User Throughput, Latency, and Packet Loss.

Area Level: As the spatial area under consideration grows, the correlation between User Density and User Throughput weakens due to factors such as load balancing, cell overlap, and macro diversity.

- **Spatial Scale Matters:** The impact and correlation of KPIs can vary significantly depending on the spatial scale. It indicates the robustness of area level data.
- **KPI Correlation:** Network KPI are closely interrelated with one another. Hence, the use of multi-variant plays a vital role.
- **Feature/KPI for QoS:** User satisfaction highly related to the speed / throughput, which is responsible for quality of service and is good choice for feature selection.

3.6 4G Network KPIs

The fourth-generation (4G) mobile network, also known as Long-Term Evolution (LTE), represents a significant advancement in mobile communication technology. Unlike its predecessors, 4G is an all-IP-based network designed to deliver higher data rates, reduced latency, and seamless connectivity for various multimedia services. The primary objective of 4G networks is to enhance user experience by supporting a wide range of applications such as high-definition video streaming, online gaming, and Internet of Things (IoT) services.

3.6.1 KPI Analysis

LTE optimization involves the analysis of key performance indicators (KPIs) to ensure efficient network performance and alignment with user expectations. These KPIs are categorized into six main subgroups:

- **Accessibility:** Measures the ability of users to access requested services under specific conditions and the quality of availability when needed. Metrics include network access requests, voice call setups, and data exchanges.

- **Retainability:** Evaluates the network's ability to maintain user connections and continue providing services without drops.
- **Mobility:** Assesses the network's capability to manage user movement while maintaining ongoing services.
- **Integrity:** Measures the reliability of the network in delivering consistent performance, focusing on metrics such as throughput, latency, and the number of users served.
- **Availability:** Checks whether the network is operational and ready to provide services to users at any given time.
- **Utilization:** Monitors the network's capacity usage to ensure that resources are not exhausted and can effectively handle user demands.

3.6.2 Network KPI Considered for Experiment

To optimize LTE performance, a set of advanced KPIs provides deeper insights into network health by focusing on traffic, user experience, and throughput. These KPIs can be mapped to their respective subgroups to facilitate targeted analysis and optimization.

Accessibility KPIs

- S1_SIG_SUCC (S1 Signaling Success Rate): Measures the success rate of signaling messages over the S1 interface. High success rates indicate efficient control plane communication between the eNodeB and core network.
- CSSR (Call Setup Success Rate): Indicates the percentage of successful call setups out of total attempts. A high CSSR is essential for providing reliable voice services.

Retainability KPIs

- TOTAL_DOWNTIME: Tracks the total time the network or specific cells were unavailable. Reducing downtime is critical for maintaining high network availability.

Mobility KPIs

- Metrics related to mobility are typically used to monitor user handovers and service continuity during movement but are not specifically outlined in this section.

Integrity KPIs

- DL_LATENCY (Downlink Latency): Measures the delay experienced by data packets in the downlink path. Lower latency is essential for real-time applications like voice and video calls.

- DL_PACK_LOSS_RATE (Downlink Packet Loss Rate): Reflects the percentage of packets lost during transmission in the downlink. Low packet loss rates are critical for ensuring service quality.

Availability KPIs

- TOTAL_DOWNTIME: Also relevant under availability KPIs, highlighting the network's operational readiness to serve users.

Utilization KPIs

- Traffic: Represents the total data transmitted over the network, helping assess the need for capacity upgrades.
- DL_TRAFFIC_MB (Downlink Traffic in MB): Measures the total data sent from the network to users, reflecting demand for data services.
- UL_TRAFFIC_MB (Uplink Traffic in MB): Tracks data sent from users to the network, offering insights into user-generated content and application usage.
- UL_QPSK_PROPORTION: Indicates the proportion of uplink traffic transmitted using Quadrature Phase Shift Keying (QPSK) modulation. Higher values may suggest challenging radio conditions.
- DL_QPSK_PROPORTION: Represents the proportion of downlink traffic using QPSK modulation. A high proportion indicates lower signal quality.
- DL_256QAM_PROPORTION: Shows the percentage of downlink traffic transmitted using 256-QAM modulation, indicating high signal quality and efficient spectrum usage.
- Avg_Usr (Average User Throughput): Measures the average data rate experienced by users during their sessions. Higher values indicate better user experience and network efficiency.
- Max_Usr (Maximum User Throughput): Represents the peak throughput achieved by a user, providing insights into network capacity and ideal conditions.
- Avg_Usr_TP_UL (Average User Throughput in Uplink): Measures the average uplink data rate experienced by users.
- Avg_Usr_TP_DL (Average User Throughput in Downlink): Tracks the average downlink data rate experienced by users, essential for evaluating download speeds and streaming quality.

Chapter 4

Methodology

In this chapter, we will discuss the details of the methodology which will give a clear understanding of different phases in the forecasting workflow, from data preparation through model development to performance evaluation. The systematic approach incorporates feedback loops for continuous optimization, ensuring robust model performance in telecommunications network analysis. We will explore various data normalization techniques, feature selection strategies, and the significance of proper train-test splitting in time series data. We will then delve into time series analysis methods, examining factors impacting model accuracy such as seasonality patterns, data characteristics, and evaluation metrics. Finally, we will explore different types of forecasting models including ARIMA[37], LSTM[54][28], GRU[8], and SVM[33], along with their hybrid implementations[6][43]. Special attention will be given to hyper-parameter tuning and model behavior under combined conditions, providing insights into how these models can be effectively fused for enhanced prediction accuracy in telecom applications.

4.1 Model Design

The proposed methodology implements a systematic approach to data collection, data analysis, model development, and performance evaluation. This process integrates both quantitative analysis and iterative feedback loops to ensure optimal performance. Each stage is carefully designed to address key challenges in predictive modeling and ensure the deployment of a robust forecasting solution, as illustrated in Figure 4.1.

4.1.1 Input Data

For this analysis, we have considered telecom network performance data from 4 different areas consisting of both urban (area 2 & area 3) and suburban (area 1 & area 4) areas. The areas are adjacent and have completely different sizes and patterns of performance as described in the figure 4.2. Area 1 has 72 base stations serving 612 cells, Area 2 has 129 base stations serving 742 cells, Area 3 comprises 106 base stations serving 642 cells, and Area 4 has 99 base stations serving 527 cells. The datasets demonstrate significant performance variations, with Area 2 showing 25% higher downlink throughput despite having fewer sites while managing 30% higher

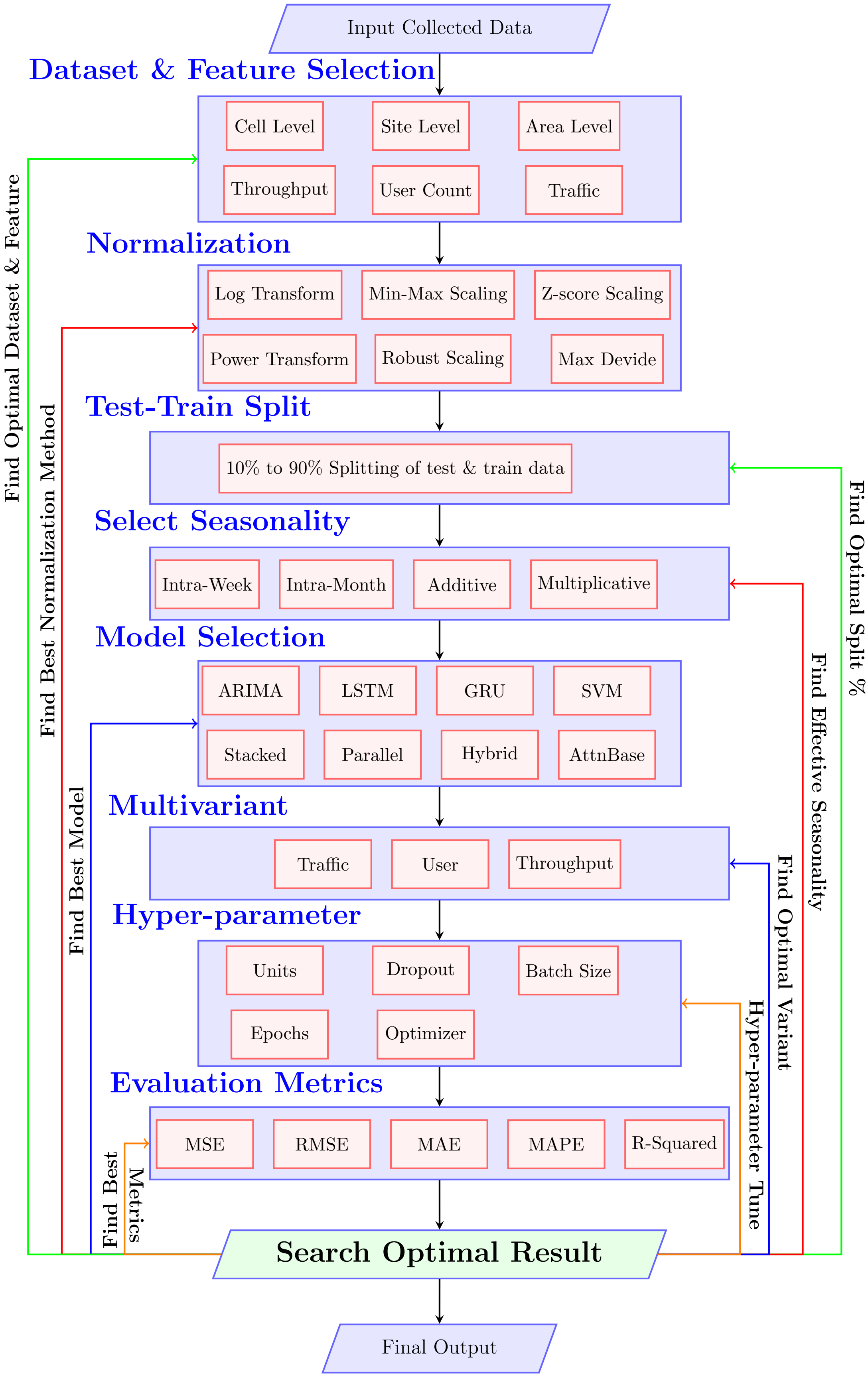

Figure 4.1: Methodology

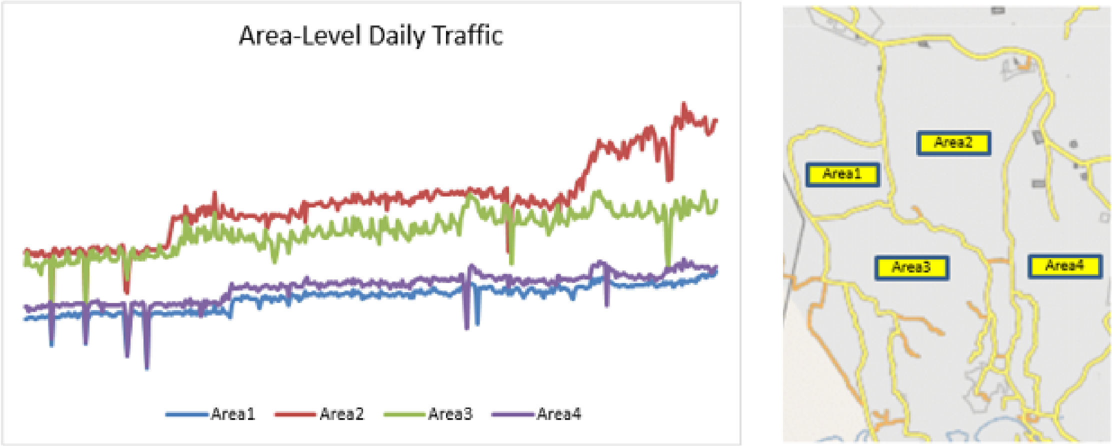

Figure 4.2: Experimental Scenario

average user load. The dataset spans over 12 months, with zero missing values across all KPIs, providing unique insights into network behavior under varying conditions and enabling robust comparative analysis in real-world network environments.

For this analysis, telecom network performance data has been gathered from four distinct areas, covering both urban (Area 2 & Area 4) and suburban (Area 1 & Area 3) regions. Urban areas in Bangladesh, such as Area 2 and Area 4, are densely populated with commercial hubs, offices, and industrial zones. The residents primarily work in corporate jobs, business sectors, and industries, leading to high daytime network demand. These areas have high-rise buildings, advanced road networks, and modern infrastructure, with higher land prices and rapid real estate development.

In contrast, suburban areas (Area 1 & Area 3) feature agricultural land, small-scale businesses, and local markets. People here are engaged in farming, retail, and public sector jobs, with peak network usage in the evening. Infrastructure is more spread out, with lower land costs and limited high-rise development, resulting in moderate network utilization with stable performance trends.

Additionally, rural areas, which were not part of this dataset, typically have low population density, scattered settlements, and minimal commercial infrastructure. The primary occupations include agriculture, fisheries, and cottage industries, leading to less reliance on digital communication during working hours. Network usage in rural regions is generally lower than in suburban areas, with spikes during the evening and night when people return home.

While rural, suburban, and urban areas exhibit distinct lifestyles across different timeframes, their Key Performance Indicator (KPI) patterns remain similar, with rural areas showing only lower overall utilization. Since this dataset is analyzed on a daily level, the detailed hour-by-hour variations are not reflected, but the overall trends provide valuable insights into network behavior across different geographic settings.

Dataset Features

Area	Site	Cell	Type
Area1	72	612	Urban
Area2	129	742	Suburb
Area3	106	642	Suburb
Area4	99	527	Urban

Figure 4.3: Variation of the Dataset

- **Real Network Data**: Collected from operational cellular networks
- **Data Span**: 366 days of continuous monitoring
- **Geographic Coverage**: 4 different areas
- **Area Classification**: 2 Urban and 2 Suburban locations
- **KPI Diversity**: 15 unique Key Performance Indicators
- **Varied Network Size**: Different cell sizes and configurations

Date	EUTRANCELL FDD	Site	AVG_NO_USER	AVG_USR_THRPUT_DL	AVG_USR_THRPUT_UL	CSSR	DL_256QAM_PROPORTION	DL_LATENCY	DL_PACK_LOSS_RATE	DL_QPSK_PROPORTION	DL_TRAFFIC_MB	MAX_NO_USER	S1_SIG_SUCC	TOTAL_DOWNTIME	TOTAL_TRAFFIC	UL_QPSK_PROPORTION	UL_TRAFFIC_MB
1-Sep-22	UVWXY48LA	UVWXY48	0.31	0.44	1	0.19	0.66	0.15	0	0.11	0.73	0.28	0.38	0	0.62	0	0.27
1-Dec-22	UVWXY62LC	UVWXY62	1	0	0.05	1	0	1	1	0.22	1	1	1	0	1	0.22	1
1-Mar-23	UVWXY28LF	UVWXY28	0	1	0.15	0	0.27	0.06	0.14	1	0	0	0	0.8	0	0.98	0
1-Jun-23	UVWXY30LA	UVWXY30	0.19	0.24	0	0.83	1	0	0.29	0	0.52	0.16	0.31	1	0.43	1	0.17

Figure 4.4: Sample Normalized Dataset

4.1.2 Data Collection and Privacy Challenges

Collecting telecom network performance data for this research involved several technical and confidentiality challenges, primarily due to the commercially sensitive nature of network KPI data. One of the key difficulties was ensuring data accessibility while maintaining operator confidentiality and competitive intelligence protection. The network KPI data includes critical performance metrics, network configuration information, and operational parameters, which are subject to strict non-disclosure agreements and operator security policies.

To address confidentiality concerns, data anonymization techniques were applied, ensuring that operator-identifying information was properly masked. Additionally, generalized performance metrics rather than specific network configuration details were used in the analysis, preventing any risks of competitive intelligence leakage. A significant challenge was securing operator approvals and navigating data-sharing agreements while ensuring that the research complied with Bangladesh's telecom regulatory framework regarding network information security.

Despite these challenges, rigorous confidentiality measures were implemented, ensuring that the dataset remained both appropriately secured and suitable for analysis without compromising operators' competitive positions in the market.

4.1.3 Data Transformation

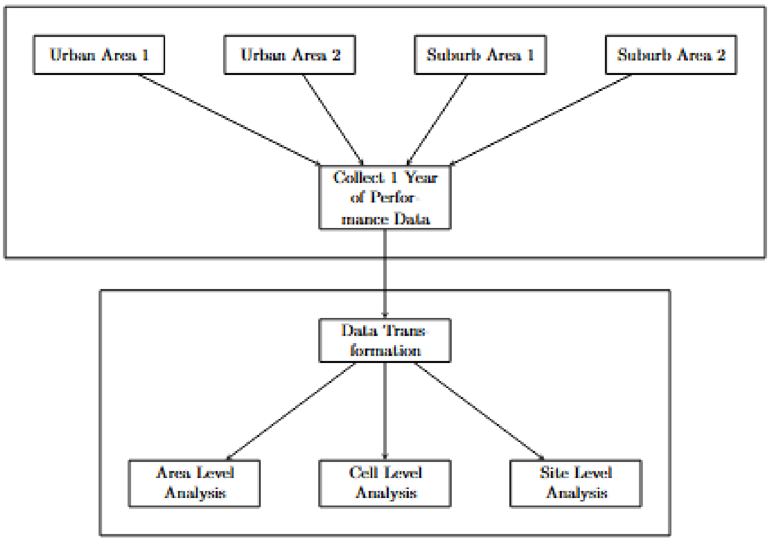

Figure 4.5: Data Collection and Transformation

This section describes the transformation of network data across different geographical levels as show in 4.5. The process starts with cell-level data collected daily over one year from urban and suburban areas. All areas use the same performance indicators (KPIs) measured during the same time periods. Before any data transformation cell, site, and thana (area) named were modified in a way that it remains anonymous.

The first step creates site names from cell names to enable site-level analysis. For each site, we combine data from all its cells daily. We sum the normal KPIs across cells, while rate-based KPIs are averaged to maintain network behavior patterns. This process is repeated for each day in the dataset.

The next step transforms site-level data to thana level. Following the same principle, we sum normal KPIs from all sites within a thana and average the rate KPIs. This approach preserves the meaning of different types of performance measures while providing a clear view of network performance at each geographical level. This transformation method allows us to analyze network performance consistently across cell, site, and thana levels while maintaining the integrity of our performance measurements.

4.1.4 Data Analysis and Feature Selection

The initial phase of the methodology focuses on preparing the raw data and identifying the most relevant features for the predictive model. This phase involves a structured workflow that ensures the dataset is optimized for training, reducing noise and improving accuracy.

The process begins with the collection of raw data from various network sources, including performance logs, alarms, and KPIs. The raw dataset typically contains inconsistencies, missing values, and irrelevant fields that require addressing during pre-processing.

We perform a comparative analysis of various cell-level, site-level, and area-level data points to determine the most significant features. The process incorporates expert opinions from network engineers to ensure selected features align with real-world scenarios and business needs. Implementation includes techniques such as Recursive Feature Elimination (RFE) and Mutual Information to enhance feature selection quality.

Multiple data normalization techniques are implemented to standardize the dataset. This normalization ensures equal weighting of all features and consistent scaling, which is essential for optimizing model performance. The methodology employs iterative testing of techniques including Min-Max Scaling, Z-score normalization, and Robust Scaling to identify the optimal approach.

4.1.5 Model Development and Evaluation

The second phase encompasses the development of multiple forecasting models, incorporation of seasonal patterns, and hyperparameter tuning for optimal performance. This phase includes iterative improvements based on systematic feedback loops.

The methodology incorporates dataset division into training, validation, and testing sets to ensure model generalization capabilities. Various data split ratios undergo testing to identify optimal combinations that maximize model performance.

Implementation includes various machine learning and deep learning models for network event forecasting. The tested models range from traditional statistical approaches like ARIMA to advanced machine learning models such as Support Vector Regression (SVR) and deep learning architectures including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU).

The methodology includes analysis of recurring seasonal patterns, examining both weekly and monthly trends that may influence network behavior. Integration of these patterns enhances the model's forecasting accuracy across different time intervals.

Ensemble learning techniques are employed to combine multiple model variants, improving overall performance. The methodology utilizes bagging, boosting, and stacking to construct robust combined models that outperform individual implementations.

Extensive hyper-parameter optimization is performed using techniques such as Grid Search, Random Search, and Bayesian Optimization to identify optimal parameter configurations for each model.

4.1.6 Model Optimization Strategies

This stage of our modeling process centers on meticulous model optimization. We systematically explore a wide range of variations across key model development steps to identify the optimal configuration. This iterative process involves systematically testing different combinations of techniques, such as data normalization methods, data split ratios, hyperparameter values, dataset selections, feature engineering approaches, and model architectures. By rigorously evaluating the performance of each combination, we aim to pinpoint the best-fit attributes that yield the most accurate and robust predictive model.
The methodology incorporates several critical feedback loops for iterative improvement:

Table 4.1: Summary of Feedback Loops

Loop Type	**Objective**	**Techniques**
Normalization	Find optimal normalization method	Min-Max, Z-score, Robust Scaling, Unit Vector, Power Transform, MaxDivide
Data Split	Determine best split ratio	Train-test-validation splits (10%–90%)
Hyperparameter	Optimize model parameters	Units, dropout, batch size, epochs, optimizer (100+ combinations)
Dataset	Select optimal data set	Cell-wise, Site-wise, Area-wise analysis
Feature	Identify key features	User metrics, Traffic patterns, Throughput
Model	Select best architecture	SVM, GRU, LSTM, ARIMA

4.1.7 Performance Assessment

The final phase focuses on comprehensive model evaluation using various accuracy metrics. Models undergo validation against real-world network data to ensure practical applicability.

Trained models undergo evaluation using multiple accuracy metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared. Comparative analysis determines which model or combination provides optimal forecasting accuracy.

The methodology concludes with a comprehensive comparison of different model architectures, hyperparameters, and data pre-processing techniques. Selection criteria prioritize models demonstrating the highest accuracy and stability across various datasets.

The methodology produces a robust, optimized forecasting model ready for deployment. Final validation against real network data ensures accurate prediction of future network behavior and effective reduction of network alarms. This systematic approach ensures the development of models that are both accurate and reliable for real-world application in network alarm reduction, while maintaining rigorous academic standards and reproducibility.

4.1.8 Forecasting with Time Series Analysis

Time series analysis[19][23] is a powerful tool that enables organizations to gain valuable insights and make informed decisions across various fields. Key applications include:

Forecasting and Prediction: Time series analysis leverages historical data to predict future values and trends[41]. This predictive capability supports data-driven decision-making, resource allocation, and strategic planning based on projected demand patterns.

Trend Analysis: By identifying and analyzing temporal patterns, time series analysis reveals long-term trends[46] and shifts. Understanding these trends aids stakeholders in strategic decision-making and future planning by providing insights into variable changes over time and their magnitudes.

Seasonal Pattern Identification: Seasonal variations are prevalent in industries such as retail, tourism[47], and agriculture. Time series analysis helps detect and anticipate these recurring patterns, enabling organizations to adjust production schedules, optimize inventory management, and plan marketing strategies according to seasonal demand fluctuations.

Anomaly Detection: Time series analysis is essential for identifying unexpected deviations or anomalies[56] in data sets. This capability is critical for detecting fraudulent activities, monitoring system performance, and identifying unusual operational behaviors across various sectors.

Financial Analysis: In finance, time series analysis supports stock price modeling, market trend forecasting, investment portfolio management, and risk assessment. Historical pattern analysis provides investors with insights into potential market movements, enabling informed investment strategies and better risk management.

Environmental Monitoring: Time series analysis plays a crucial role in environmental studies by examining variables such as weather patterns[46], air quality, and water levels over time. It helps researchers identify trends, predict future conditions, and inform decision-making for environmental conservation and management. Applications include climate pattern prediction, pollution impact assessment, and water resource monitoring.

4.2 Components of Time Series Data

Time series data consists of observations recorded at specific time intervals, capturing how variables evolve over time. Key characteristics include:

Temporal Ordering: Time series data is inherently chronological, with each observation recorded sequentially. This temporal order is vital for detecting and analyzing trends, patterns, and cyclic behaviors.

Time Dependency: Observations in a time series are not independent but exhibit sequential dependencies. The value at a given point often depends on prior observations, reflecting the influence of past events on current conditions.

Irregular Sampling: Time series analysis becomes complex when data is recorded at uneven intervals or when observations are missing. Addressing these challenges requires specialized techniques to manage irregular[58] or incomplete data points for accurate modeling and forecasting.

Time series data can be decomposed into key components to better understand its underlying patterns and behavior:

Trend: The trend component reflects the long-term progression of the data, indicating its overall direction over time. Trends may exhibit linear patterns, which are steady increases or decreases over time, or nonlinear behavior, which includes fluctuating or curved movements reflecting more complex dynamics.

Seasonality: Seasonality[47] captures recurring patterns that occur at regular intervals, such as daily, weekly, monthly, or annual cycles. It also includes influences from external factors such as weather changes, holidays, or economic fluctuations.

Noise (Random Fluctuations or Irregularities): Noise represents random and unpredictable variations in the data that cannot be attributed to trend or seasonality. Contributing factors may include measurement errors and random events or unknown influences.

4.3 Overview of Different Types of Time Series Models

Time series models are essential statistical tools used to analyze and forecast data that evolves over time. These models help identify underlying patterns, trends, and relationships within the data, enabling informed predictions of future outcomes. Below is an overview of commonly used time series models[20]:

- Moving Average (MA) – Uses weighted past error terms to predict future values[42]
- Autoregressive (AR) – Predicts based on linear combinations of past observations[42]

- Autoregressive Moving Average (ARMA) – Combines AR and MA components for comprehensive analysis[42]

- Autoregressive Integrated Moving Average (ARIMA) – Extends ARMA with differencing for non-stationary data[42]

- Seasonal ARIMA (SARIMA) – Enhances ARIMA with seasonal component modeling[32][48]

- Exponential Smoothing – Applies weighted averages with higher weights for recent observations

- Vector Autoregression (VAR) – Models multiple interdependent time series simultaneously[21]

- Machine Learning Models (RNN, LSTM) – Captures complex nonlinear patterns through neural networks[28]

- Support Vector Machine (SVM) – Supervised machine learning algorithm that finds optimal hyperplane to separate data classes with kernel trick for non-linear data separation and robust handling of high-dimensional data[26]

- Prophet – Decomposes series into trend, seasonality, and holiday effects with robust handling of outliers[59]

4.4 Detailed Explanation of Hyperparameters in Time Series Models

Effective time series forecasting often requires tuning model hyperparameters to capture underlying patterns accurately and improve predictive performance. This section details essential hyperparameters for popular models used in time series analysis.

4.4.1 Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model is a widely used approach for forecasting stationary and non-stationary time series data. The model is characterized by three key hyperparameters:
p, **d**, and **q**. The AR term **p** specifies the number of lag observations included, capturing linear dependence between current and past values, though higher values risk overfitting. The differencing order **d** determines how many times data is differenced to achieve stationarity by removing trends. The MA term **q** specifies the number of lagged forecast errors included, helping smooth random fluctuations by modeling relationships between forecast errors and past errors.[63]

4.4.2 Long Short-Term Memory (LSTM) Networks

LSTM models are effective for capturing long-term dependencies and complex patterns in time series data. The model is characterized by several key hyperparameters:
The **units** specify the number of LSTM cells per layer, where more units capture complex patterns but increase computational complexity and risk overfitting. The **batch_size** determines the number of training samples processed before updating weights, with smaller batches making training dynamic while larger batches improve stability and convergence speed. The **dropout** represents the fraction of neurons randomly set to zero during training, preventing overfitting by reducing network dependency on specific neurons. The **learning_rate** controls the step size for weight updates during training, where a low rate slows convergence while a high rate risks overshooting optimal solutions. The **epochs** specify the number of times the training dataset is passed through, where too few result in underfitting while too many can lead to overfitting.[63][57]

4.4.3 Gated Recurrent Unit (GRU) Networks

GRUs are simplified versions of LSTMs, with fewer parameters, faster training times, and similar capabilities. The model employs several hyperparameters:
The **units** determine the number of GRU cells per layer, **batch_size** controls the number of samples per gradient update, **dropout** sets the fraction of units zeroed during training, **learning_rate** defines the step size for weight updates, and **epochs** specify the number of training dataset passes.[57]

4.4.4 Support Vector Regression (SVR)

SVR is a machine learning approach that fits the data by finding a hyperplane within a defined margin. The model's key hyperparameters include:
The regularization parameter **C** controls the trade-off between low error and model simplicity, where higher values focus on fitting data points but risk overfitting, while lower values improve generalization. The **epsilon** parameter specifies the margin of tolerance for prediction errors, balancing complexity and accuracy by ignoring small fluctuations. The **kernel** type (linear, polynomial, RBF, sigmoid) determines the function for mapping data to higher-dimensional space, affecting the model's ability to capture non-linear relationships. The **gamma** parameter defines the influence range of training examples in non-linear kernels, where high values fit close points but risk overfitting, while low values produce smoother fits. The **degree** of polynomial kernel function allows modeling complex relationships, though higher degrees may overfit with excessive complexity.[35]
Careful hyperparameter tuning ensures telecom professionals can optimize forecasting models to predict service demand, manage network resources efficiently, and enhance customer experience.

4.5 Seasonality in Time Series Analysis

Seasonality refers to recurring patterns in time series data observed at regular intervals due to factors such as weather changes, economic cycles, or social events. In the telecommunications sector, seasonal variations may include increased data usage during weekends, holidays, or special events.

- **Intra-Week Seasonality**: Recurring patterns that occur on specific days of the week, repeating every week. These trends are often influenced by cultural, social, or business-related factors.[1]
- **Intra-Month Seasonality**: Recurring trends tied to specific dates within a month, such as spikes in activity on the 1st, 15th, or 30th of each month.[40]

These patterns are critical in time series modeling and can be captured using techniques such as Fourier Transforms, seasonal decomposition, or machine learning models like ARIMA, SARIMA, or LSTM with seasonality features.

- **Additive Seasonality**: Seasonal effects remain constant over time and are added to the trend.[29]

$$Y(t) = T(t) + S(t) + e(t) \tag{4.1}$$

- **Multiplicative Seasonality**: Seasonal effects change proportionally with the trend.[29]

$$Y(t) = T(t) \times S(t) \times e(t) \tag{4.2}$$

These findings have direct implications for telecom network operations. The ability to anticipate and prepare for seasonal variations in network demand allows for more strategic planning and resource allocation. This improved forecasting capability supports both short-term operational decisions and long-term infrastructure planning, ultimately contributing to more efficient and reliable network services.

4.6 Time Series Data Splitting Methodology

Our research employed a systematic trial-and-error approach to determine the optimal data split for telecom network analysis and prediction. Rather than implementing complex splitting techniques like rolling windows or multiple cross-validation strategies, we focused on finding the most effective simple chronological split ratio. Through iterative testing, we explored various proportions of training and testing data, ultimately evaluating the model's performance with splits ranging from 80% training - 20% testing of the chronologically ordered data.

Data Split Optimization: The decision to use a straightforward chronological split was driven by the unique characteristics of telecom network data. Telecom networks exhibit distinct patterns in their performance metrics, and maintaining these temporal relationships proved crucial for model accuracy. By testing different split ratios, we could assess how the length of historical data used for training impacted the model's ability to predict future network behavior.

Model Evaluation Process: For each split ratio tested, we evaluated the model's performance using standard metrics while considering the specific requirements of telecom network prediction. The 80-20 split emerged as particularly effective, providing sufficient historical data for the model to learn network patterns while maintaining a substantial testing period to validate predictions. This approach aligned well with the temporal nature of network performance data and the practical requirements of telecom infrastructure planning.

Practical Implementation: Our methodology prioritized simplicity and effectiveness over complexity. The straightforward chronological split eliminated potential complications that could arise from more sophisticated splitting techniques, making the model more practical for real-world implementation in telecom network analysis.

4.7 Evaluation Metrics for Time Series Forecasting

Selecting the right evaluation metric is crucial for assessing the performance of time series forecasting models. The choice of metric depends on business goals, data characteristics, and tolerance for different types of errors.

4.7.1 Primary Metrics

The Mean Squared Error (MSE) served as a fundamental metric in our analysis, calculated as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4.3}$$

This metric proved particularly valuable for our telecom data analysis as it effectively penalized large prediction errors, which are critical in network capacity planning. The Root Mean Squared Error (RMSE), derived from MSE, provided error measurements in the same units as our network metrics:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4.4}$$

4.7.2 Percentage-Based Metrics

We utilized the Mean Absolute Percentage Error (MAPE) to understand relative prediction accuracy:

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4.5}$$

MAPE expressed errors as percentages of actual values, offering insights into the model's relative performance across different scales of network metrics. However, we noted its limitations when dealing with near-zero values in certain network parameters. The Symmetric Mean Absolute Percentage Error (SMAPE) helped address these limitations:

$$\text{SMAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{(|y_i| + |\hat{y}_i|)/2} \tag{4.6}$$

4.7.3 Model Fit Assessment

The Coefficient of Determination (R^2) played a crucial role in evaluating our models' explanatory power:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}i)^2}{\sum i = 1^n (y_i - \bar{y})^2} \tag{4.7}$$

This metric helped us understand how well our models captured the variance in network performance data. For scenarios involving exponential growth patterns in network usage, the Mean Squared Logarithmic Error (MSLE) provided valuable insights:

$$\text{MSLE} = \frac{1}{n}\sum_{i=1}^{n}\left(\log(1 + y_i) - \log(1 + \hat{y}_i)\right)^2 \tag{4.8}$$

Our choice of metrics was guided by the specific requirements of telecom network analysis. We prioritized metrics that could effectively capture both large-scale network events and subtle performance variations. The combination of these metrics provided a comprehensive framework for evaluating our models' predictive capabilities, ensuring reliable forecasts for network planning and optimization. Each metric offered unique insights: MSE and RMSE for absolute error magnitude, MAPE and SMAPE for relative error assessment, R^2 for model fit quality, and MSLE for handling exponential growth patterns in our data. Selecting an appropriate evaluation metric ensures effective model tuning and reliable performance assessment for specific business and forecasting objectives.

4.8 Fused Models for Time Series Forecasting

Combined models leverage the strengths of multiple models to improve forecasting accuracy by capturing both linear and nonlinear patterns, long-term dependencies, and seasonality in time series data. By integrating different techniques, combined models can offer robust solutions for complex forecasting tasks that may be difficult for standalone models.

Our investigation focused on three principal combined model architectures. The LSTM-ARIMA combination leveraged LSTM's capacity for capturing nonlinear dependencies while incorporating ARIMA's strength in modeling linear trends. This integration proved particularly effective for our telecom data, where both linear and nonlinear patterns coexist. The LSTM-GRU architecture balanced computational efficiency with predictive accuracy, while the LSTM-SVM combination enhanced boundary condition handling in our predictions. The implementation of these architectures is visually represented in Figure 4.8, which demonstrates the interconnection between different model components.

4.8.1 Layered Model Structures

The implementation of stacked[34] architectures revealed interesting performance characteristics. Our three-layer models, incorporating combinations of LSTM, GRU, and SVM, demonstrated superior capability in capturing hierarchical patterns within the network data. The two-layer variants offered a more computationally efficient alternative while maintaining acceptable prediction accuracy for less complex network metrics. The structural organization of these layered models is detailed in Figure 4.6.

Stacked 3 Layer: A three-layer structure of LSTM, GRU, or SVM, capturing complex data hierarchies and dependencies.

Stacked 2 Layer: A simpler structure with two layers, effective for moderately complex datasets.

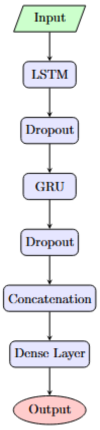

Figure 4.6: Block Diagram of Stacked Combined Model

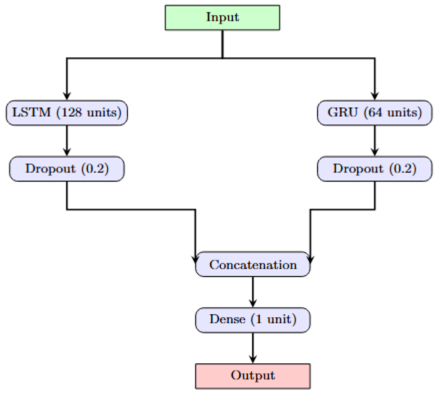

Figure 4.7: Block Diagram of Parallel Combined Model

4.8.2 Hybrid Layer Models

Hybrid models[16] combine different architectures to enhance model flexibility and adaptability. An illustration of a stacked combined model is shown in Figure 4.8.

Hybrid 2 Layer: Combines models like LSTM and GRU, balancing computational efficiency and prediction accuracy.

Hybrid 3 Layer: Integrates multiple layers and models, offering improved predictive power for highly dynamic environments.

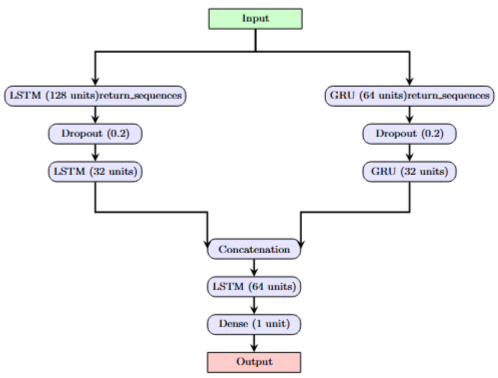

Figure 4.8: Block Diagram of Hybrid Combined Model

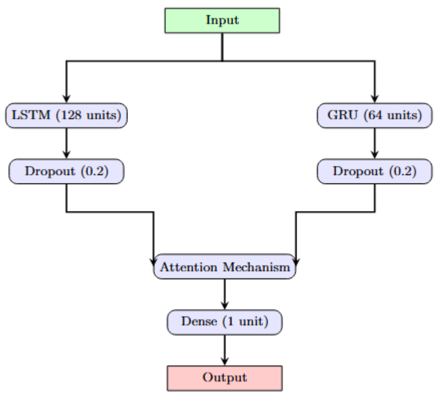

Figure 4.9: Block Diagram of Attenuation Based Combined Model

4.8.3 Attention-Based Models

Attention mechanisms prioritize the most relevant parts of the time series data, improving forecasting accuracy by focusing on critical temporal information[36]. An illustration of a stacked combined model is shown in Figure 4.9.

Attention-Based LSTM: Incorporates attention layers to enhance LSTM's ability to capture essential temporal patterns.
Attention-Based GRU: Combines attention mechanisms with GRU for efficient temporal feature extraction.
Hierarchical Attention-Based: Models multiple hierarchical levels of attention to capture both local and global dependencies.
Self-Attention Based: Focuses on relationships within the sequence itself, enabling powerful pattern recognition across time steps.

The combination of multiple modeling approaches offered several distinct advantages in our analysis. By integrating complementary model strengths, we achieved enhanced prediction accuracy through error reduction. This hybrid approach demonstrated increased robustness against data fluctuations and noise, a common challenge in telecom network data. The combined architecture exhibited superior generalization capabilities, adapting effectively to the dynamic nature of network performance patterns. Furthermore, the integration of multiple models reduced overfitting risk by averaging predictions from diverse modeling approaches.

4.9 Normalization and Its Significance on Model Accuracy

Normalization is the process of transforming data to a consistent scale, ensuring that all features contribute proportionally to a model's performance. In time series analysis, normalization is critical because features with different ranges or units can dominate the learning process, leading to biased or suboptimal results.

4.9.1 Normalization Techniques

Normalization significantly enhances model accuracy through multiple mechanisms. It ensures fair feature consideration in pattern recognition, enabling better identification of seasonality and trends. Complex architectures like neural networks benefit from consistent input scales, preventing gradient-related issues. The optimization process becomes more efficient, leading to faster convergence and better parameter estimation. Most importantly, normalization improves generalization by preventing individual features from dominating the learning process, reducing overfitting and enabling more robust predictive capabilities.
Min-Max Scaling: Transforms data to a fixed range, typically [0, 1].
Formula:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{4.9}$$

Standardization (Z-Score Scaling): Centers data around zero and scales it to unit variance.

Formula:

$$X' = \frac{X - \mu}{\sigma} \tag{4.10}$$

Where μ is the mean and σ is the standard deviation.
Robust Scaling: Centers data using the median and scales it based on the interquartile range (IQR).
Formula:

$$X' = \frac{X - \text{median}}{\text{IQR}} \tag{4.11}$$

Unit Vector Normalization (L2 Norm): Scales data so that the Euclidean norm (L2 norm) equals 1.
Formula:

$$X' = \frac{X}{|X|} \tag{4.12}$$

Where

$$|X| = \sqrt{\sum X_i^2} \tag{4.13}$$

is the L2 norm.
Power Transformer (Yeo-Johnson Transformation): Stabilizes variance and makes data more Gaussian-like.
Formula: Adjusts based on the power parameter λ. Automatically determines λ for optimal transformation.
MaxDivide Scaling: Divides each value by the maximum value in the feature.
Formula:

$$X' = \frac{X}{X_{\text{max}}} \tag{4.14}$$

The choice of normalization technique is guided by data characteristics and modeling needs. Min-Max scaling suits bounded data, while standardization is optimal for Gaussian distributions. Robust scaling handles outlier-rich datasets using median and IQR. Unit vector normalization prioritizes directional relationships over magnitude. Power transformers address non-linear, skewed distributions through parameter optimization. MaxDivide scaling offers a simple solution for naturally bounded data with known maximums.

Chapter 5

Experimental Design and Data Analysis

In this chapter, experimental outcomes will be discussed and insights will be provided for selecting time series forecasting approaches in telecommunications. We analyze various forecasting methodologies applied to telecom data, comparing their effectiveness and practical implications. Key contributions include prioritizing area-level data for general forecasting, emphasizing expert-driven feature selection, and recommending data normalization for privacy and accuracy. Experiments highlight the superiority of LSTM and GRU models, with combined models achieving over 90% accuracy. Weekly seasonality and hyper-parameter tuning significantly improve results, while R-squared is recommended for accuracy evaluation. The findings offer a step-by-step framework, uniquely tailored to telecom predictive analysis.

5.1 Dataset Selection

Data set selection was confirmed based on both network KPI data behavior and forecasting accuracy.

5.1.1 Dataset Analysis from Domain Expert

Randomness in cell-level KPI and impact of deployment: Figure 5.1 illustrates the randomness observed in cell-level KPIs, highlighting the inconsistency in traffic patterns among different cells within the same site. Figure 5.1 and Figure 5.2 provide a comprehensive analysis of this phenomenon. In Figure 5.1, the varying trends in daily traffic among cells within a site demonstrate the inherent randomness in cell-level performance. And Figure 5.2 further underscores the randomness by showcasing how network deployment can lead to both increases and decreases in the traffic of existing cells, emphasizing the unpredictable nature of cell-level KPIs. These findings collectively highlight the need for robust network planning and management strategies to accommodate the inherent randomness in cell performance.

- Inconsistent behavior of cells within the same site: Cells under the same site may perform differently without any additional cells being introduced. Cells are following normal growth as no new cells are added to the site in the later part of the time period.

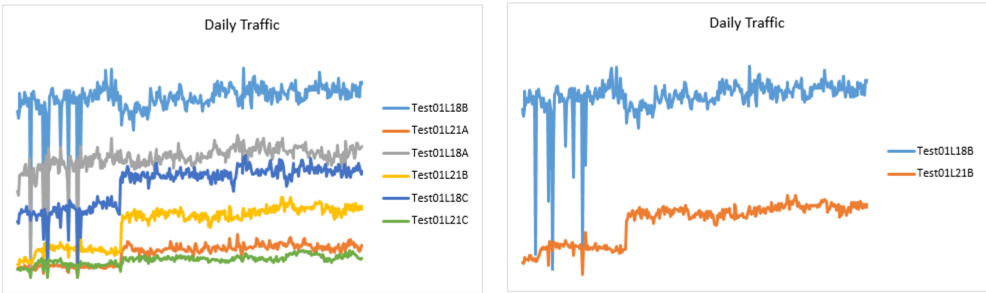

Figure 5.1: Different cells of the same site following different patterns

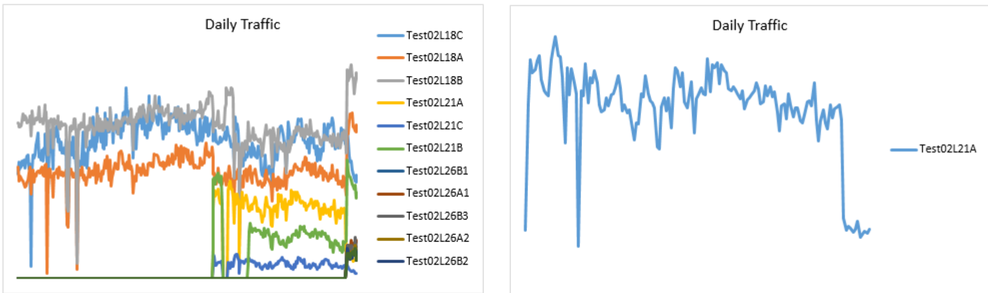

Figure 5.2: Increase and decrease of existing cell traffic due to network deployment

- Randomness in cell-level KPI and impact of deployment: The deployment of new network components can introduce randomness into cell-level Key Performance Indicators (KPIs).

Randomness in site-level KPI and impact of deployment: Figure 5.3 and 5.4 illustrates the randomness observed in site-wise KPIs, highlighting the inconsistency in traffic, throughput, and user patterns across different sites. Figure 5.3 and figure 5.4 offer a comprehensive analysis of this phenomenon. Infigure 5.3, the varying trends in daily traffic, throughput, and user activity among the five sites demonstrate the inherent randomness in site-wise performance. On the otherhand,figure 5.4 explores the impact of a new site on existing site traffic, revealing that the introduction of a new site can lead to both increases and decreases in the traffic of existing sites. Figure 5.4 further underscores the randomness by showcasing how sites within the same Thana (area) can exhibit distinct patterns, suggesting that geographical proximity does not guarantee consistent behavior. Finally, figure 5.4 highlights the dynamic nature of site traffic, demonstrating that network deployment can result in both increases and decreases in existing site traffic. These findings collectively emphasize the unpredictable nature of site-wise KPIs, emphasizing the need for robust network planning and management strategies to accommodate the inherent randomness in site performance.

Area-Level Traffic Behavior: Area-level (Thana) traffic growth demonstrates a general increasing trend, often correlating with the growth in nearby areas. Despite fluctuations at the cell level, the overall traffic momentum at the Thana level remains steady.

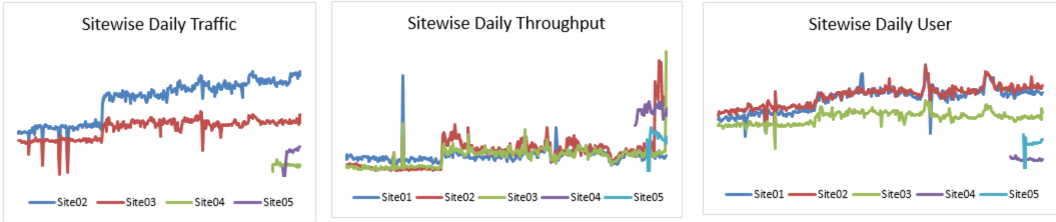

Figure 5.3: Different site of same Thana (area) following different pattern

Figure 5.4: Effects of Network Deployment on Existing Site Traffic

- Consistency of Area level KPI: Figure 5.5:Despite fluctuations in cell-level traffic, the overall traffic trend at the Thana level continues to maintain its momentum, indicating the resilience of area-level traffic growth patterns.
- Robustness of Area level KPI: Figure 5.6: Even with increased traffic in adjacent areas, the area-level traffic remains stable, highlighting that localized traffic growth does not always destabilize neighboring areas.

5.1.2 Findings from Forecasting Techniques

Experimental Setup:
Forecasting models (ARIMA, LSTM, GRU, SVM, GRU-SVM) are applied to user, traffic, and throughput features for cell, site, and area level data. Figure 5.7 presents a comparison of Mean Squared Error (MSE) values for different forecasting models (ARIMA, LSTM, GRU, SVM, GRU-SVM) applied to user, traffic, and throughput data at three different aggregation levels: cell, site, and area.

Experimental Results:
Across all three forecasting targets (user, traffic, throughput), the area level consistently shows the lowest MSE values for most models. This suggests that aggregating data at the area level improves forecast accuracy and consistency compared to cell or site-level data.

- **Cell Level:** Exhibits the highest variability and MSE values, highlighting the challenge of accurately forecasting individual cell behavior due to localized noise and inconsistencies.
- **Site Level:** Shows improved consistency compared to cell level data, but still higher variability than area level data.

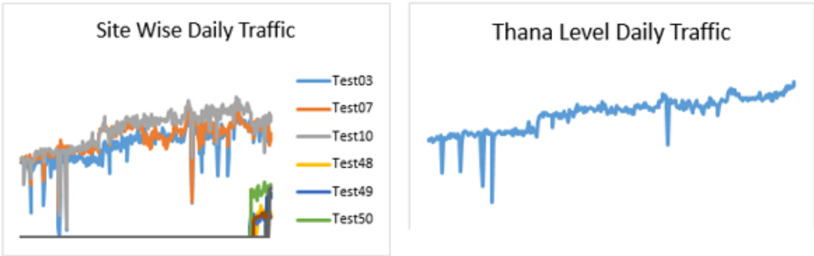

Figure 5.5: Consistent Thana Level Traffic Despite Fluctuations in Site Traffic

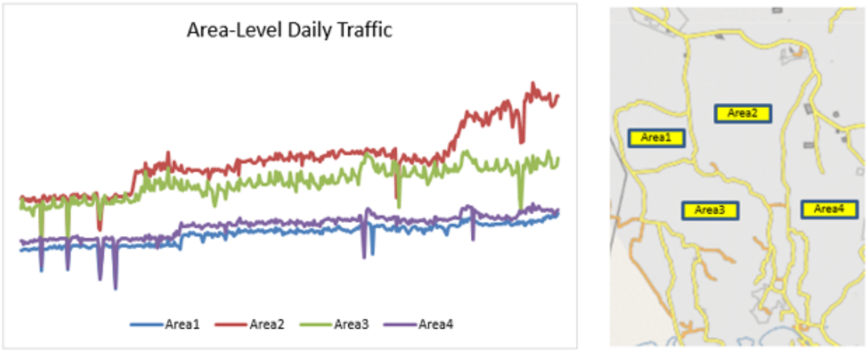

Figure 5.6: Area level traffic maintained despite of increase of traffic in adjacent areas

- **Area Level:** Demonstrates the lowest variability and highest consistency across all models and forecasting targets.

Insight on Dataset Selection: Analysis of forecasting performance across different network hierarchies reveals significant insights into optimal data aggregation levels for prediction accuracy. Area-level forecasting consistently demonstrates superior performance, evidenced by lower MSE values compared to cell and site-level predictions. This enhanced accuracy stems from the aggregation process, which creates a more stable and predictable baseline by smoothing out localized fluctuations and noise that typically affect individual cells or sites. The area-level approach also offers practical advantages by simplifying the modeling process through a reduction in the number of independent time series that require analysis and forecasting. This streamlined approach proves particularly valuable for strategic network planning and resource allocation, as it provides a comprehensive and stable view of network traffic and user demand patterns across broader geographical regions.

While site and cell-level forecasting exhibit higher variability and generally lower accuracy, they remain invaluable for specific operational purposes. These granular predictions excel at identifying unusual traffic patterns and network anomalies that might be obscured in higher-level aggregations. They also play a crucial role in capacity planning by enabling fine-tuned allocation based on localized demand patterns. Furthermore, these detailed forecasts facilitate effective troubleshooting by providing specific insights into network performance issues at individual network elements.

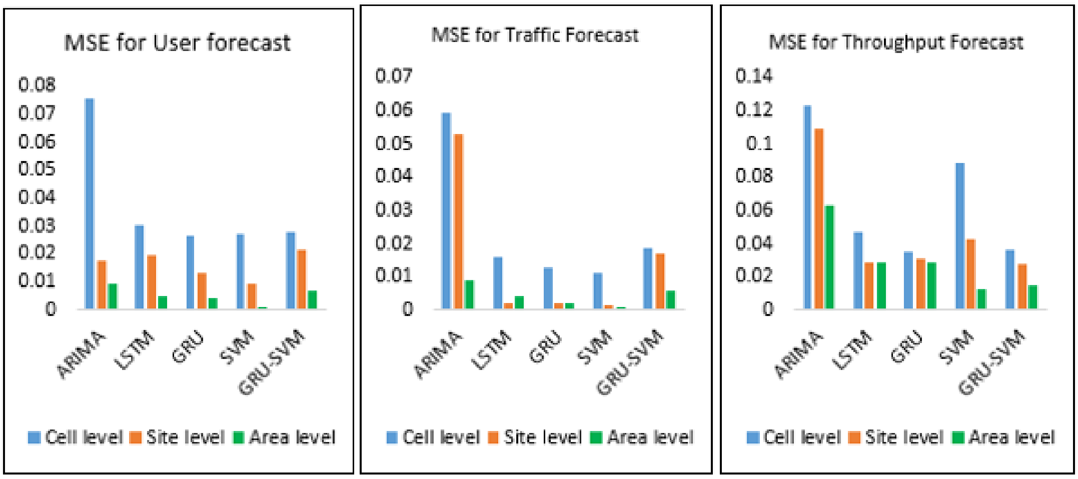

Figure 5.7: MSE for Cell, Site, and Area Level Prediction

Based on these findings, we recommend prioritizing area-level data for primary forecasting activities, particularly for strategic planning and resource allocation decisions. However, this should be complemented by targeted cell and site-level analysis when detailed operational insights are required. To maximize forecasting accuracy at all levels, it is essential to consider the interconnected nature of network elements, accounting for the influence of neighboring cells and sites in the analysis process. This holistic approach ensures both broad strategic accuracy and detailed operational effectiveness in network planning and management.

5.2 Feature Selection Analysis for Network Quality Prediction

5.2.1 Experimental Setup

To illustrate the importance of feature selection in telecom network analysis, we conducted a comparative study examining the relationship between device quality and network performance. The experiment contrasts two scenarios: a premium device (iPhone) with poor network coverage and an unknown brand phone with excellent network coverage, as shown in Figure 5.8. Table 5.1 presents a comprehensive comparison of user experiences across different criteria, demonstrating that network quality supersedes device quality in determining user satisfaction.

Criteria	**iPhone User**	**Unknown Brand User**
Phone Quality	Happy	Sad
Network Signal	Sad (1 bar)	Happy (Full bars)
Data Speed	Poor	Excellent
Media Quality	Blurry	Clear
Call Quality	Distorted	Smooth
Overall Experience	Unsatisfactory	Satisfactory

Table 5.1: Comparison of User Experience Based on Device and Network Quality

5.2.2 Experimental Results

The analysis reveals a striking contrast between device quality and actual user experience. As illustrated in Figure 5.9, the impact of network performance is clearly visible in media quality, where even a premium device produces blurry images under poor network conditions, while a basic device achieves crystal-clear quality with strong network connectivity. Despite having a higher-end device, the iPhone user experiences consistent service quality issues due to poor network conditions: blurry media sharing, buffering videos, and distorted calls. Conversely, the unknown brand phone user enjoys superior service quality across all metrics due to excellent network coverage. This disparity highlights that network performance metrics, particularly throughput, are more critical determinants of user experience than device specifications.

Figure 5.8: Device Comparison: Premium vs Basic Phone Network Experience

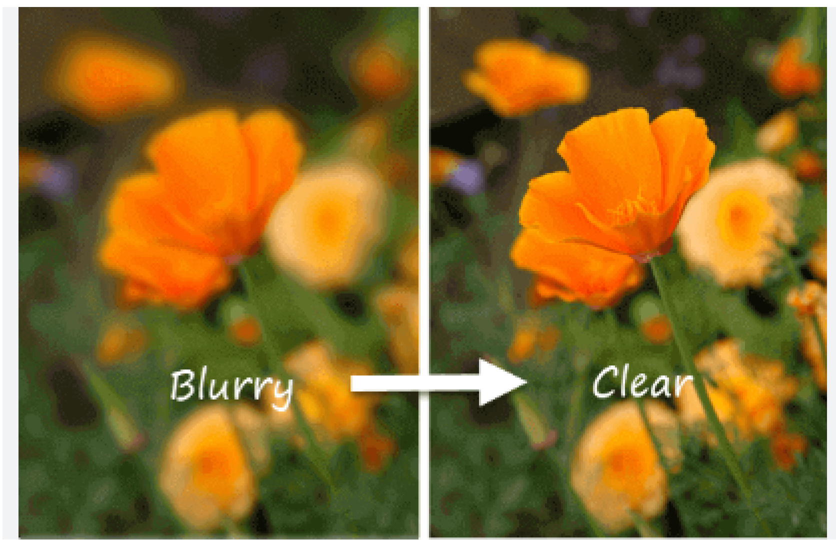

Figure 5.9: Impact of Network Quality on Media Clarity

5.2.3 Insights on Feature Selection

The comparative analysis offers crucial insights for selecting key performance indicators in telecom network forecasting. The stark contrast between device quality and service experience demonstrates that network performance metrics, particularly throughput, should be prioritized over device-specific considerations. This finding has significant implications for network operators focusing on quality of service optimization. The visual evidence of network impact on media quality - from blurry to clear images - provides a tangible demonstration of how throughput directly affects user experience. While traditional metrics like traffic volume and user count offer contextual information, throughput emerges as the most crucial KPI for several reasons: it directly correlates with user experience quality, provides immediate feedback on network performance, and enables proactive service quality management. For telecom operators, this insight suggests that focusing on throughput prediction and optimization can yield more significant improvements in user satisfaction than attempting to accommodate various device capabilities. The consistent pattern observed across different service aspects - from image sharing to voice calls - validates the technical consensus that throughput serves as the most reliable predictor of network service quality.

5.3 Analysis on Data Normalization Techniques

Experimental Setup

Different data normalization techniques were applied to a telecommunication network dataset to identify the best fit for improving model performance. Figure 5.10 presents a bar graph titled "R-Squared Value", illustrating the effect of various data scaling techniques on the model's performance. The x-axis displays the scaling techniques: Min-Max Scaling, Standardization, Robust Scaling, Unit Vector, Power Transformer, and MaxDivide. The y-axis represents the R-squared value, which indicates the proportion of variance in the dependent variable explained by the independent variable(s) in a regression model.

Experimental Results

Table 5.2: Comparison of Normalization Techniques Based on Metrics using GRU model

Normalization Technique	MSE	RMSE	MAE	R-Squared
Min-Max Scaling	0.000276439	0.01662645	0.012596577	0.930816133
Standardization	0.080217155	0.283226332	0.171212034	0.720524907
Robust Scaling	0.010244505	0.101215142	0.073200246	0.907379856
Unit Vector	0.0000000423	0.000205636	0.000205636	0.0
Power Transformer	0.192797452	0.439087067	0.23228411	0.645750683
MaxDivide	0.000642688	0.025351286	0.021315623	0.681670023

The results demonstrate the performance of various normalization techniques, evaluated using key metrics such as Mean Squared Error (MSE), Root Mean Squared

Error (RMSE), Mean Absolute Error (MAE), and R-Squared values. The analysis reveals significant variations in the impact of each normalization technique on model accuracy and performance.

Among the tested methods, **Min-Max Scaling** emerged as the most effective normalization technique, yielding the lowest error metrics and the highest R-squared value, as found from Figure 5.10. This suggests that Min-Max Scaling was highly efficient in normalizing telecommunication network data, which often contains well-defined ranges of numerical features such as signal strength, latency, and bandwidth utilization.

Standardization and **Robust Scaling** also delivered competitive results. Standardization performed particularly well for metrics like RMSE and MAE, with an R-squared value indicating a reasonable model fit. Robust Scaling, known for its ability to handle outliers, exhibited strong performance but lagged slightly behind Min-Max Scaling in error reduction.

Interestingly, the **Power Transformer** and **MaxDivide** techniques provided moderate results, indicating their potential utility for specific use cases within telecommunication network analysis. However, the **Unit Vector** normalization yielded poor R-squared results, suggesting it may not be suitable for predictive models in this context, particularly when dealing with regression tasks involving network performance metrics.

These findings underscore the variability in the effectiveness of normalization techniques, with Min-Max Scaling being the most suitable for this particular dataset.

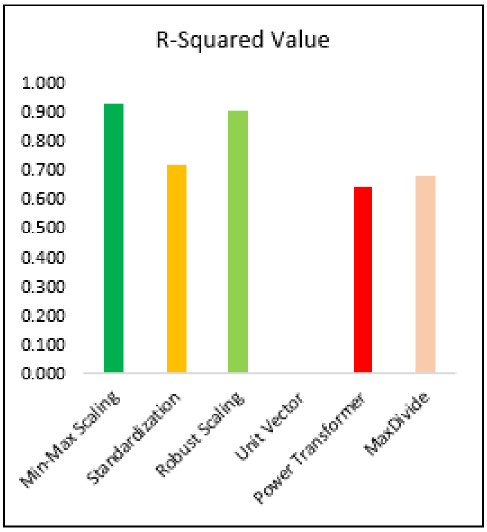

Figure 5.10: R-Squared Value for Different Data Normalization Techniques using GRU model

Insights on Using Normalization Techniques:

Normalization plays a crucial role in preprocessing telecommunication network data, as it ensures that features with different scales contribute equally to the model. The choice of the normalization technique depends on the nature of the data and the modeling objective.

The results underscore the critical importance of tailoring normalization methods to align with the unique characteristics of telecommunication network data. Effective normalization not only enhances the predictive power of forecasting models but also ensures that the inherent patterns within the data are preserved for meaningful interpretation. Among the evaluated techniques, Min-Max Scaling demonstrated superior performance, achieving the optimal balance between minimizing error metrics and maintaining the interpretability of model outputs. This makes it particularly suitable for scenarios where the range of numerical features, such as latency, bandwidth utilization, or signal strength, is well-defined and bounded.

However, it is essential to acknowledge that no single normalization technique is universally optimal. Forecasters should adopt a flexible and iterative approach to preprocessing, carefully selecting and testing multiple normalization methods based on the specific dataset at hand. Factors such as the presence of outliers, the distribution of the data, and the intended forecasting application must guide this decision. For example, techniques like Robust Scaling are more appropriate for datasets with significant outliers, while methods like Power Transformation are advantageous for addressing skewed distributions commonly observed in telecommunication metrics during peak usage periods.

Furthermore, practitioners should prioritize conducting exploratory data analysis (EDA) to gain an in-depth understanding of the dataset's structure and variability. Such analysis can inform the choice of the most suitable normalization technique, ensuring that the forecasting model is both accurate and generalizable. By adopting this systematic approach, forecasters can address the unique challenges posed by real-world telecommunication networks and develop models that deliver robust and actionable predictions.

5.4 Analysis on Data Splitting

5.4.1 Experimental Setup

The experiment was designed to evaluate the impact of different training data ratios on model performance for traffic throughput prediction. We systematically varied the training data proportion from 10% to 90%, maintaining the same testing methodology across all experiments. The model's performance was assessed using Mean Squared Error (MSE) and R-squared metrics across three datasets: training, validation, and test sets. This comprehensive evaluation approach allows us to understand both the model's learning capacity and its generalization ability under different data splitting conditions.

5.4.2 Experimental Results

Table 5.3 presents the detailed performance metrics across different training data ratios. The results shows that, the optimal train-validation-test split appears to be around 50-60% for training data, as this range consistently shows high R-squared values across all three datasets (training, validation, and test) while maintaining low

MSE values.
Looking at the performance metrics across different train percentages, we can observe a classic pattern of model fitting behavior: below 30% training data, negative R-squared values indicate severe underfitting; from 30-70%, the model achieves optimal fit with balanced performance across training, validation, and test sets; while beyond 80%, the divergence between training and test R-squared values suggests the beginning of overfitting as the model performs progressively worse on unseen data.

Table 5.3: Performance Metrics Across Different Training Data Ratios Using SVM model

Train (%)	**Training**		**Validation**		**Test**	
	MSE	R-Squared	MSE	R-Squared	MSE	R-Squared
10	0.039	-0.399	0.067	-0.396	0.058	-0.445
20	0.049	-1.341	0.034	0.030	0.037	-0.993
30	0.004	0.812	0.004	0.876	0.004	0.681
40	0.003	0.868	0.004	0.895	0.005	0.494
42	0.002	0.895	0.004	0.895	0.005	0.460
45	0.003	0.852	0.004	0.888	0.005	0.422
50	0.002	0.895	0.004	0.889	0.005	0.426
60	0.004	0.847	0.005	0.886	0.006	0.446
70	0.002	0.892	0.004	0.857	0.004	0.619
80	0.004	0.363	0.003	0.663	0.006	0.188
90	0.007	0.013	0.004	0.242	0.005	0.286

5.4.3 Insights on Data Splitting Ratios

The analysis of different data splitting ratios provides valuable insights for both general forecasting applications and specifically for telecom network KPI forecasting. In general forecasting scenarios, our results demonstrate that the conventional wisdom of using larger training sets doesn't always yield optimal results. The peak performance achieved with 50-60% training data suggests that having a balanced distribution between training and validation/test sets can be more beneficial than allocating a larger portion to training, as shown in Table 5.3. This finding challenges the traditional approach of using 80-90% of data for training, particularly in time series forecasting where the temporal dynamics and patterns play crucial roles. In the specific context of telecom network KPI forecasting, this insight becomes even more relevant due to the dynamic nature of network traffic patterns. The results indicate that using a more balanced data split allows the model to better capture both the long-term patterns in the training data and the recent trends in the validation set, leading to more robust predictions. This is particularly important in telecom networks where traffic patterns can exhibit both seasonal trends and sudden changes, making it crucial to maintain sufficient data in both training and validation sets for effective model development and evaluation.

5.5 Different Model Performance Analysis

5.5.1 Experimental Setup

The experimental framework was designed to evaluate and compare four distinct machine learning models for network KPI prediction: Support Vector Machine (SVM), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and ARIMA. The evaluation was conducted across three critical network elements: user behavior, throughput performance, and traffic patterns. To ensure comprehensive assessment, we employed multiple performance metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared (R^2) values.

5.5.2 Experimental Results

The experimental results demonstrate varied performance patterns across different network elements and models. Tables 5.4, 5.5, and 5.6 present detailed performance metrics for each combination of model and network element.

Table 5.4: Comparison of Model Performance Metrics for User prediction

Model	MSE	MAE	MAPE	RMSE	R-squared
SVM	0.00213	0.04615	0.03577	4.90000	0.71577
GRU	0.00017	0.01320	0.00986	1.23000	0.92871
LSTM	0.00083	0.02873	0.02582	6.99000	0.66687
ARIMA	0.00940	0.09697	0.06853	12.75000	-0.15886

Table 5.5: Comparison of Model Performance Metrics for Throughput Prediction

Model	MSE	MAE	MAPE	RMSE	R-squared
SVM	0.00351	0.05927	0.03158	5.32000	0.86762
GRU	0.01204	0.10972	0.06308	14.00000	0.81320
LSTM	0.00730	0.08544	0.04890	61.41000	0.86631
ARIMA	0.06291	0.25083	0.15156	24.64000	-0.37949

Table 5.6: Comparison of Model Performance Metrics for Traffic Prediction

Model	MSE	MAE	MAPE	RMSE	R-squared
SVM	0.00064	0.02520	0.02243	2.56000	0.52283
GRU	0.00020	0.01420	0.01171	4.46000	0.85731
LSTM	0.00075	0.02735	0.02027	10.83000	0.87910
ARIMA	0.00885	0.09409	0.08625	9.55000	-5.29163

For user prediction (Table 5.4), the GRU model demonstrates exceptional performance with the lowest MSE (0.00017) and highest R^2 value (0.92871). This represents a significant improvement over traditional approaches, with GRU showing particular strength in capturing user behavior patterns. The LSTM model follows as the second-best performer, while ARIMA shows notably poor performance with negative R^2 values.

In throughput prediction (Table 5.5), SVM emerges as the leading model with an R^2 value of 0.86762, closely followed by LSTM at 0.86631. This suggests that both linear and non-linear modeling approaches can effectively capture throughput patterns. However, the significantly higher RMSE of LSTM (61.41%) compared to SVM (5.32 Traffic prediction results (Table 5.6) show strong performance from both LSTM and GRU models, achieving R^2 values of 0.87910 and 0.85731 respectively. These models demonstrate superior capability in capturing complex traffic patterns, with GRU showing particularly low MSE (0.00020) despite a slightly lower R^2 value than LSTM.

5.5.3 Insights on Model Selection

The analysis reveals several key insights for both general forecasting applications and specific telecom network KPI predictions:

The analysis of model performance reveals significant insights for forecasting applications in both general and telecom-specific contexts. In general forecasting scenarios, deep learning approaches, particularly GRU and LSTM, demonstrate consistent superiority over traditional statistical methods in capturing complex patterns and maintaining high R^2 values. The selection between GRU and LSTM models should be carefully considered based on specific requirements of response time and accuracy, as GRU often achieves comparable performance while offering lower computational complexity. The consistent underperformance of ARIMA across all metrics highlights its limitations in handling the complex, non-linear patterns prevalent in modern network data.

In the context of telecom network KPI forecasting, our analysis reveals distinct patterns in model effectiveness across different prediction tasks. User behavior prediction shows optimal results with GRU models, which excel at capturing short-term patterns and user dynamics effectively. For throughput prediction, the best results emerge from hybrid approaches that combine the strengths of both traditional methods like SVM and modern techniques such as LSTM. Traffic prediction demands more sophisticated deep learning approaches, with both LSTM and GRU demonstrating superior capability in capturing the complex interdependencies inherent in network traffic patterns. These findings underscore the importance of tailoring model selection to specific KPI characteristics rather than adopting a one-size-fits-all approach to network forecasting.

These findings emphasize the importance of selecting models based on specific KPI characteristics rather than applying a universal approach. The results also suggest that modern deep learning techniques, particularly GRU and LSTM variants, are better suited for the complexity of contemporary telecom network forecasting tasks. However, traditional methods like SVM still maintain relevance for specific metrics, particularly in throughput prediction where linear patterns may be more prominent.

5.6 Fusion Model Evaluation and Analysis

5.6.1 Experimental Setup

The experimental evaluation focused on fused model architectures using network KPI data collected over 12 months. The dataset underwent preprocessing to handle missing values and was normalized using min-max scaling. We implemented a sliding window approach with a 24-hour window size and 1-hour prediction horizon. The fused models were developed using PyTorch and trained on an NVIDIA Tesla V100 GPU. The training utilized Adam optimizer with a 0.001 learning rate and 64 batch size, incorporating early stopping with 10 epochs patience to prevent overfitting. Performance evaluation employed multiple metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared values.

5.6.2 Experimental Results

Table 5.7: Comparison of Fused Model Performance

Model	MSE	MAE	MAPE	RMSE	R-squared
GRU-SVM	0.00520	0.07180	0.05350	6.92000	0.33920
LSTM-SVM	0.00530	0.07290	0.05430	7.00000	0.32020
GRU-ARIMA	0.01070	0.10350	0.07380	9.30000	-0.39610
LSTM-ARIMA	0.01120	0.10580	0.07720	9.67000	-0.45780
Stacked 3 Layer	0.00200	0.04450	0.02990	25.35000	0.90100
Stacked 2 Layer	0.00120	0.03450	0.02510	27.83000	0.94880
Hybrid 2 Layer	0.00100	0.03200	0.02270	28.58000	0.95600
Hybrid 3 Layer	0.00230	0.04830	0.03580	25.87000	0.88310
Attention Based-LSTM	0.00810	0.09010	0.05130	21.21000	0.59280
Attention Based-GRU	0.00680	0.08250	0.04700	22.08000	0.65940
Hirarchial Attention Based	0.00960	0.09780	0.05240	20.06000	0.52070
Self Attention Based	0.00080	0.02820	0.02240	28.90000	0.96020
Hierarchical-LSTM only	0.00080	0.02740	0.02260	5.05000	0.96770
Hierarchical-LSTM+GRU	0.00100	0.03220	0.02410	5.81000	0.95540

The experimental results highlight the superior performance of various fused model architectures in network KPI forecasting. As shown in Table 5.7, the hierarchical and attention-based approaches demonstrate significant improvements in prediction accuracy. The Hierarchical-LSTM only model achieves exceptional performance with an R-squared value of 0.9677 and an MSE of 0.0008, indicating high prediction accuracy. The Self Attention Based model shows comparable excellence with an R-squared value of 0.9602. Hybrid architectures display strong performance, with the 2-layer variant achieving an R-squared value of 0.9560 and the 3-layer variant maintaining robust accuracy with 0.8831. The fusion of different model types, such as GRU-SVM and LSTM-ARIMA, shows varied performance, suggesting that architectural choice significantly impacts prediction quality.

5.6.3 Insights on Using Fused Model Performance

From a general forecasting perspective, our results demonstrate that fused models offer distinct advantages in time series prediction. The hierarchical attention-based architecture's superior performance in capturing both short-term and long-term dependencies is evidenced by the Hierarchical Attention Based model's consistent performance across all metrics. The Self Attention Based model's remarkable MSE of 0.0008 showcases the effectiveness of attention mechanisms in identifying relevant historical patterns. The successful integration of different architectural elements in the Hierarchical-LSTM+GRU model, achieving an R-squared value of 0.9554, demonstrates the potential of combining complementary approaches for robust forecasting.
In the specific context of telecom network KPI forecasting, the fused models exhibit particular strengths in handling network data characteristics. The Hierarchical-LSTM only model's superior RMSE of 5.05% and highest R-squared value demonstrate its effectiveness in capturing the hierarchical nature of network metrics. The low MAPE values across hybrid architectures indicate high prediction accuracy crucial for network resource management. The strong performance of both 2-layer and 3-layer hybrid variants suggests effective complexity management while maintaining accuracy. These results indicate that fused models are particularly suited for telecom network KPI forecasting, offering improved accuracy and reliability for network management, proactive maintenance, and resource optimization.

5.7 Impact of Seasonality Patterns on Network KPI Forecasting Accuracy

5.7.1 Experimental Setup

The experiment investigates the impact of different seasonality patterns on forecasting accuracy for three key network elements: User metrics (Usr), Throughput (TP), and Traffic. For each network element, we evaluated three different seasonality configurations: no seasonality, weekly seasonality, and monthly seasonality. The analysis uses R-squared values as the primary metric for model performance assessment, as shown in Table 5.8. The experiment aims to quantify the improvement in forecasting accuracy when incorporating different types of seasonal patterns, particularly focusing on the distinction between weekly and monthly cycles in network behavior.

5.7.2 Experimental Results

The analysis reveals significant variations in the impact of seasonality across different network elements, as illustrated in Figure 5.11. For User metrics, incorporating weekly seasonality resulted in the highest R-squared value of 0.8868, representing a 15.50% improvement over the no-seasonality baseline. Throughput measurements similarly benefited from seasonal patterns, achieving an R-squared value of 0.9234 with weekly seasonality, marking a 7.52% improvement. Traffic patterns showed a more complex relationship with seasonality, where weekly patterns provided only

NE Type	Seasonality	R-Squared	Improvement
Usr	No Seasonality	0.7678	-
	Weekly	0.8868	15.50%
	Monthly	0.8212	6.95%
TP	No Seasonality	0.8589	-
	Weekly	0.9234	7.52%
	Monthly	0.9109	6.05%
Traffic	No Seasonality	0.6772	-
	Weekly	0.6889	1.73%
	Monthly	0.4243	-37.35%

Table 5.8: Performance Comparison of Different Seasonality Patterns

marginal improvement (1.73%), and monthly seasonality actually degraded performance with an R-squared value of 0.4243, significantly lower than the no-seasonality baseline. These results, as presented in Table 5.8, demonstrate that the effectiveness of seasonality varies substantially across different network KPIs.

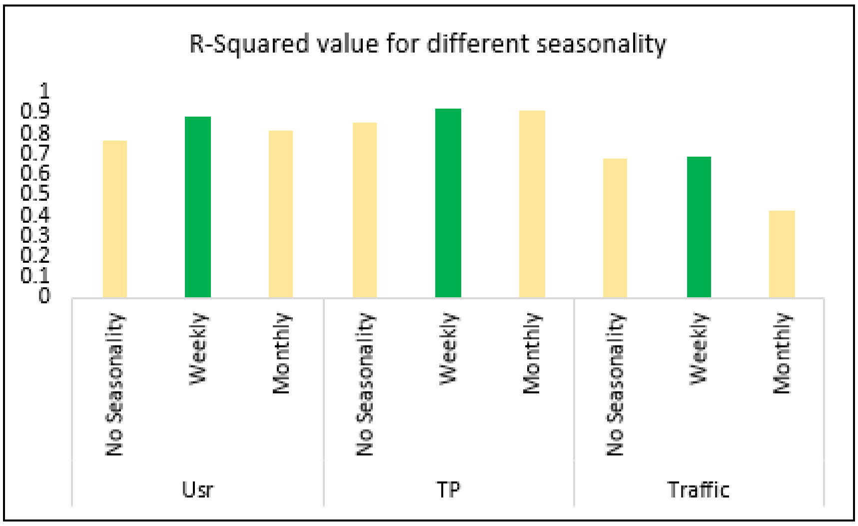

Figure 5.11: R-Squared Values for Different Seasonality Patterns

5.7.3 Insights on Seasonality Patterns

The analysis of seasonality patterns provides valuable insights for both general time series forecasting and specific telecom network KPI predictions. In general time series forecasting, the results emphasize the importance of matching seasonality patterns to the underlying data characteristics rather than applying a one-size-fits-all approach. The significant variation in improvement percentages shown in Table 5.8 demonstrates that blindly incorporating seasonality without understanding the data's inherent patterns can be counterproductive. For telecom network KPI forecasting specifically, the strong performance of weekly seasonality patterns across user metrics and throughput suggests a dominant weekly cycle in network usage patterns. This aligns with typical user behavior where network usage follows weekly routines tied to business and leisure activities. The degraded performance of monthly seasonality in traffic patterns indicates that some network metrics may be driven more by short-term factors than monthly cycles. These findings have direct implications for network capacity planning and resource allocation, suggesting that operators should prioritize weekly patterns in their forecasting models for user-related metrics and throughput, while potentially avoiding monthly seasonal adjustments for traffic predictions. The substantial improvement in R-squared values for user metrics (15.50%) and throughput (7.52%) with weekly seasonality provides strong evidence for implementing week-based seasonal adjustments in telecom forecasting systems, particularly for customer-facing performance indicators.

5.8 Impact of Other Variants on Forecasting Accuracy

5.8.1 Experimental Setup

The experimental analysis focused on evaluating the impact of different variants on forecasting accuracy across three key network KPIs: User count, Throughput, and Traffic. The study incorporated various feature combinations including DL_TRAFFIC_MB, AVG_USR_THRPUT_DL, and AVG_NO_USER as additional variants. The experiment utilized a consistent dataset and preprocessing methodology, implementing standardized evaluation metrics of R-squared values and correlation coefficients. Each variant combination was tested under identical conditions to ensure comparative validity, with the base case of 'No Variant' serving as the control scenario for performance benchmarking.

5.8.2 Experimental Results

Table 5.9: R-Squared and Correlation Values for Different Variants

Feature	**Variant**	**R-Squared**	**Correlation**
User	No Variant	0.85650	—
User	DL_TRAFFIC_MB	0.87920	0.89930
User	AVG_USR_THRPUT_DL	-6.38480	0.41270
Throughput	No Variant	0.88950	—
Throughput	DL_TRAFFIC_MB	0.82220	0.56680
Throughput	AVG_NO_USER	0.85440	0.41270
Traffic	No Variant	0.88520	—
Traffic	AVG_USR_THRPUT_DL	-5.63040	0.56680
Traffic	AVG_NO_USER	-3.74800	0.89930

The analysis of variant impact reveals significant variations in forecasting performance, as illustrated in Figure 6.10 and detailed in Table 5.9. For User forecasting, the inclusion of DL_TRAFFIC_MB improved the R-squared value from 0.8565 to 0.8792, demonstrating a positive impact with a strong correlation of 0.8993. However, introducing AVG_USR_THRPUT_DL led to a dramatic decrease in R-squared to -6.3848, despite maintaining a moderate correlation of 0.4127. Throughput forecasting showed more stable behavior across variants, with the base model achieving an R-squared of 0.8895, and variants showing slight degradation but maintaining positive R-squared values. Traffic forecasting exhibited the most sensitivity to variant inclusion, with both AVG_USR_THRPUT_DL and AVG_NO_USER resulting in negative R-squared values (-5.6304 and -3.7480 respectively), despite showing moderate to strong correlations.

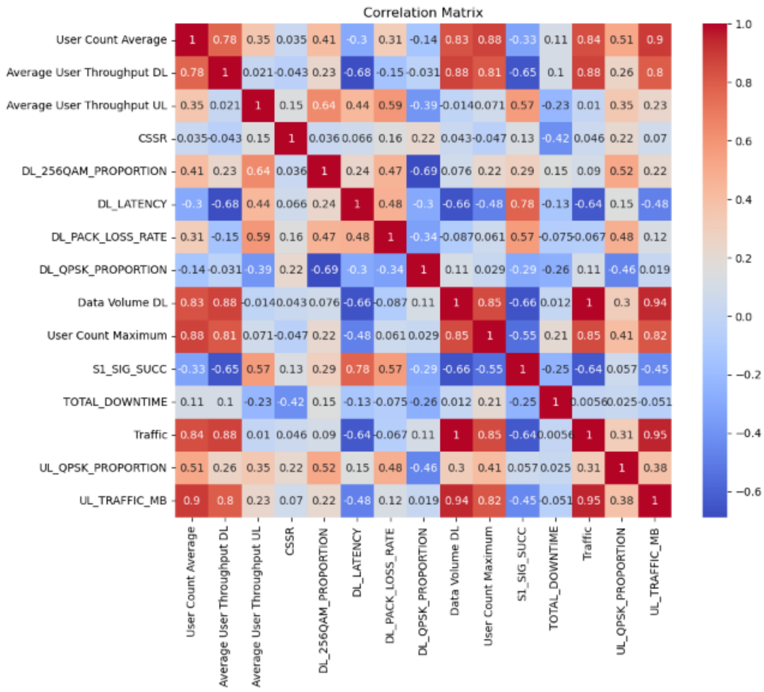

Figure 5.12: Correlation matrix between telecom network KPIs

The correlation matrix, as shown in figure 5.12, reveals the relationships between key performance indicators (KPIs) and their potential influence on telecom forecasting models. Notably, User Count Average and Maximum exhibit a strong positive correlation (0.88), aligning with UL_TRAFFIC_MB (0.9 and 0.82 respectively), suggesting a direct relationship with network usage. Conversely, DL Latency shows a negative correlation with throughput (-0.68), highlighting a potential bottleneck. These correlations can be used to develop forecasting models, where KPIs can be combined to give future network behaviors.

For User Prediction		
Other Variant (KPIs)	MSE	Correlation
UL_TRAFFIC_MB	0.005603	-0.9
Max_Usr	0.00699	-0.88
Traffic	0.005506	-0.84
DL_TRAFFIC_MB	0.006208	-0.83
UL_QPSK_PROPORTION	0.005294	-0.51
DL_256QAM_PROPORTION	0.012016	-0.41
S1_SIG_SUCC	0.025639	-0.33
DL_PACK_LOSS_RATE	0.017575	-0.31
DL_LATENCY	0.010487	-0.3
DL_QPSK_PROPORTION	0.005734	-0.14
TOTAL_DOWNTIME	0.006584	-0.11
CSSR	0.010846	-0.035
Avg_Usr_TP_UL	0.011866	0.35
Avg_Usr_TP_DL	0.005625	0.78
All	0.026557	

For Throughput Prediction		
Other Variant (KPIs)	MSE	Correlation
DL_LATENCY	0.026149	-0.68
S1_SIG_SUCC	0.0091	-0.65
DL_PACK_LOSS_RATE	0.005615	-0.15
CSSR	0.004213	-0.043
DL_QPSK_PROPORTION	0.015366	-0.031
Avg_Usr_TP_UL	0.008636	0.021
TOTAL_DOWNTIME	0.010378	0.1
DL_256QAM_PROPORTION	0.004233	0.23
UL_QPSK_PROPORTION	0.006775	0.26
Avg_Usr	0.005652	0.78
UL_TRAFFIC_MB	0.024419	0.8
Max_Usr	0.018489	0.81
Traffic	0.005095	0.88
DL_TRAFFIC_MB	0.01354	0.88
All	0.089882	

For Traffic Prediction		
Other Variant (KPIs)	MSE	Correlation
Avg_Usr	0.046251	-0.83
S1_SIG_SUCC	0.009326	-0.66
DL_LATENCY	0.017556	-0.66
DL_PACK_LOSS_RATE	0.012327	-0.087
Avg_Usr_TP_UL	0.093781	-0.014
TOTAL_DOWNTIME	0.003022	0.012
CSSR	0.005551	0.043
DL_256QAM_PROPORTION	0.022877	0.076
DL_QPSK_PROPORTION	0.012082	0.11
UL_QPSK_PROPORTION	0.00363	0.3
Max_Usr	0.030382	0.85
Avg_Usr_TP_DL	0.005728	0.88
UL_TRAFFIC_MB	0.043651	0.94
Traffic	0.005925	1
All	0.054296	

Figure 5.13: Impact of Other Variant (KPIs) on Prediction

the impact of Other Variants (KPIs) significantly influences the prediction of user behavior, throughput, and traffic patterns. As illustrated in the data shown in figure 5.13), these KPIs exhibit varying degrees of correlation and Mean Squared Error (MSE) across different prediction categories.

For user prediction, `UL_TRAFFIC_MB` and `Max_Usr` demonstrate strong negative correlations (-0.9 and -0.88 respectively) with low MSE values (0.005603 and 0.00699, respectively), indicating their significance in forecasting user-related metrics.

In throughput prediction, `DL_LATENCY` and `S1_SIG_SUCC` show moderate negative correlations (-0.68 and -0.65) with relatively low MSE (0.026149 and 0.0091, respectively), suggesting their importance in estimating network performance.

Traffic prediction identifies `Avg_Usr` and `S1_SIG_SUCC` as key indicators with high negative correlations (-0.83 and -0.66) and low MSE (0.046251 and 0.009326, respectively). Notably, for traffic prediction, the `Traffic` KPI exhibits a perfect positive correlation (1) and `UL_TRAFFIC_MB` shows a high positive correlation (0.94) with MSE of 0.005925 and 0.043651, respectively.

Using all variants simultaneously resulted in the lowest MSE (0.026557) for user prediction, as shown in figure 5.13). This indicates that adding multiple variants can significantly impact performance. However, the presence of a highly negative influence KPI can spoil or deteriorate the overall outcome, overshadowing the benefits of positively correlated variants. These findings emphasize the complex interplay of KPIs in telecom forecasting, highlighting the necessity of a multifaceted approach in predictive modeling for telecommunications networks.

5.8.3 Insights on Using Other Variants for Forecasting

From a general forecasting perspective, the experimental results demonstrate that the relationship between correlation values and forecasting accuracy is not always straightforward. High correlation coefficients, such as the 0.8993 observed with DL_TRAFFIC_MB, can indicate strong relationships between variables but may not guarantee improved forecasting performance. The significant degradation in R-squared values for certain variants suggests that multicollinearity and model complexity play crucial roles in determining the effectiveness of additional features. This observation emphasizes the importance of careful feature selection and validation in multivariate forecasting systems.

In the specific context of telecom network KPI forecasting, the results provide valuable insights for practical implementation. The positive impact of DL_TRAFFIC_MB on User forecasting (R-squared improvement to 0.8792) suggests that traffic information can enhance user behavior prediction. However, the negative impact of AVG_USR_THRPUT_DL on both User and Traffic forecasting indicates that throughput metrics should be used cautiously as additional variants.

The relatively stable performance of Throughput forecasting across variants (maintaining R-squared values above 0.82) suggests that this KPI might be more robust to feature variation. These findings highlight the importance of domain-specific feature selection in telecom network forecasting, where the interdependencies between KPIs must be carefully considered to maintain model accuracy and reliability.

The correlation matrix provides key insights into the relationships between KPIs and their impact on forecasting performance. A strong positive correlation exists between User Count Average, Maximum, and UL TRAFFIC MB (0.88 & 0.9), reinforcing their predictive power. DL Latency negatively correlates (-0.68) with Throughput, indicating a bottleneck in network performance. CSSR has the lowest correlation (-0.035) but does not have the highest MSE (0.010846), suggesting it has limited influence on forecasting outcomes but does not significantly degrade performance. Using all variants simultaneously resulted in the lowest MSE (0.026557), indicating that multiple variants can impact forecasting accuracy. However, a single highly negative influence KPI can significantly deteriorate the overall outcome, overshadowing the benefits of positively correlated variants.

UL_TRAFFIC_MB (0.005603), Max_Usr (0.00699), and Traffic (0.005506) have the lowest MSE, indicating strong predictive reliability. Conversely, DL_256QAM_PROPORTION (0.012016) and S1_SIG_SUCC (0.025639) have higher MSE, reducing forecasting effectiveness.

- **Correlation does not always equate to better forecasting** High correlation values indicate strong relationships but do not guarantee improved performance.
- **Multicollinearity & model complexity affect forecasting accuracy** Adding correlated KPIs can degrade performance if not properly validated.
- **Feature selection is crucial** DL_TRAFFIC_MB enhances User forecasting. Throughput metrics should be used cautiously. Traffic forecasting requires refined feature selection to maintain model stability.

In a nutshell, prioritizing domain-specific KPIs is essential to enhance forecasting models. Validating feature importance before inclusion helps prevent performance degradation. Additionally, using traffic-related KPIs strategically is necessary to maintain accuracy and reliability.

5.9 Hyperparameter Tuning Analysis for Network KPI Forecasting

5.9.1 Experimental Setup

We conducted extensive hyperparameter tuning experiments to optimize the forecasting model's performance. Table 5.10 presents the hyperparameter space explored during the optimization process. The experiments utilized a systematic grid search approach across different combinations of neural network architectures and training parameters. We designated 33 different hyperparameter combinations, labeled from A1 to A33, representing unique configurations from the parameter space. A1 represents the most optimized configuration while A33 represents the initial configuration, allowing us to systematically analyze the impact of different parameter combinations on model performance.

Hyperparameter	Values
Hidden Units	50, 100, 150
Dropout Rate	0.2, 0.3, 0.4
Batch Size	32, 64
Epochs	50, 100, 150
Optimizer	Adam, RMSprop

Table 5.10: Hyperparameter Space for Model Optimization

5.9.2 Experimental Results

The experimental results demonstrate significant improvements in model performance through systematic hyperparameter tuning. Figure 5.14 illustrates the progression of R-squared values across different hyperparameter combinations from A33 to A1. The graph shows three distinct phases of improvement: an initial low-performance phase (red portion) with R-squared values around 0.1, a rapid improvement phase (blue portion) where the R-squared value increases significantly, and a stabilization phase (green portion) where the model achieves optimal performance with R-squared values approaching 0.8. Starting from an initial R-squared value of 0.11, the optimization process achieved a final R-squared value of 0.76, representing a 567% improvement in predictive accuracy. Analysis of the results, as shown in Table 5.10, revealed that larger hidden units (150) combined with moderate dropout rates (0.3) generally yielded better performance. The Adam optimizer consistently outperformed RMSprop across different configurations, particularly when coupled with a batch size of 64 and training duration of 100 epochs.

5.9.3 Insights on Hyperparameter Tuning

Our comprehensive analysis yields valuable insights for both general forecasting applications and specific telecom network KPI forecasting scenarios. The progression shown in Figure 5.14 demonstrates that careful hyperparameter tuning can lead to substantial improvements in model performance. In the context of general time series forecasting, we observe that model architecture parameters, particularly the number of hidden units and dropout rates, play a crucial role in capturing temporal dependencies. The optimal configuration of 150 hidden units suggests that complex temporal patterns require sufficient model capacity for accurate prediction. For telecom network KPI forecasting specifically, our findings indicate that larger batch sizes (64) contribute to better stability in handling network traffic patterns and seasonal variations. The superior performance of the Adam optimizer aligns with the need to adapt to rapidly changing network conditions and varying scales of KPI measurements. These insights particularly benefit telecom operators in developing robust forecasting systems for network performance indicators such as throughput, latency, and resource utilization. The clear improvement pattern shown in the R-squared

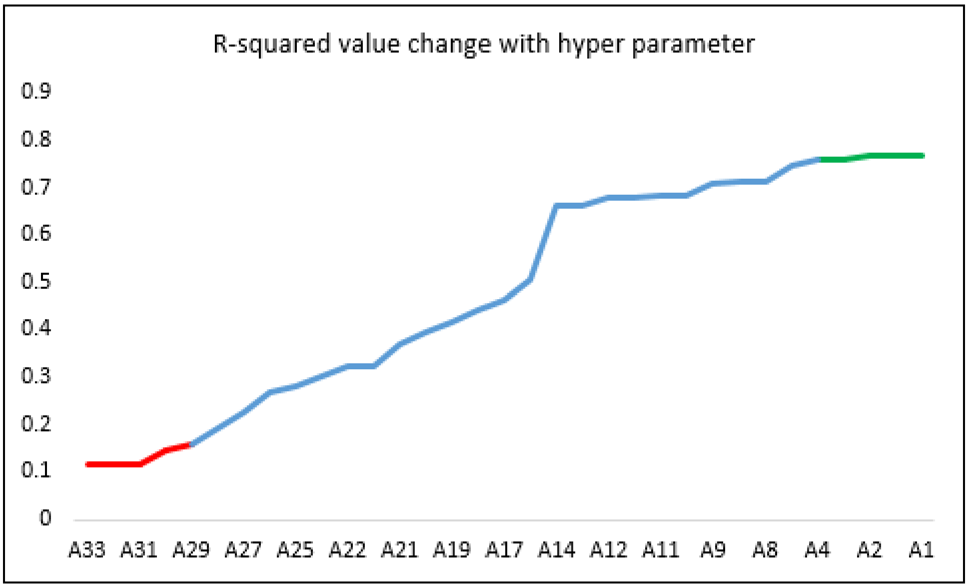

Figure 5.14: R-Squared Value for Different Combinations of Hyperparameters

progression from A33 to A1 emphasizes the importance of systematic hyperparameter optimization in achieving reliable telecom KPI forecasting models. Moreover, the moderate dropout rate (0.3) proves effective in preventing overfitting while maintaining the model's ability to capture intricate network behavior patterns. This finding is particularly relevant for telecom KPI forecasting, where the model must generalize across diverse network conditions and traffic patterns while maintaining prediction accuracy.

5.10 Analysis of Evaluation Metrics for Network KPI Forecasting

5.10.1 Experimental Setup

The experiment evaluates four different forecasting models: SVM, LSTM, GRU, and ARIMA, applied to network KPI data focusing on average user throughput. Each model was tested using both normalized and original data scales to assess the impact of data preprocessing on model performance. The evaluation utilized five key metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2). Table 5.11 presents the comprehensive comparison of these metrics across all models and data scales.

These experimental results and guidelines collectively contribute to a robust methodology for telecom network forecasting, emphasizing the critical importance of area-level data aggregation, appropriate normalization techniques, advanced model architectures, and systematic hyper-parameter optimization. The research provides network operators with clear guidelines for implementing effective forecasting systems while balancing accuracy with practical considerations. The demonstrated improvements in prediction accuracy across various metrics and scenarios suggest

Model	Scale	MSE	MAE	RMSE	MAPE	R^2
SVM	Normalized	0.04	0.20	0.11	0.19	-0.31
SVM	Original	285125.44	533.97	308.25	0.12	-0.31
LSTM	Normalized	0.01	0.12	0.07	0.21	0.31
LSTM	Original	99559.02	315.53	176.91	0.07	0.31
GRU	Normalized	0.02	0.13	0.07	0.22	0.18
GRU	Original	118535.12	344.29	194.30	0.08	0.18
ARIMA	Normalized	0.03	0.18	0.10	0.18	-0.07
ARIMA	Original	224228.11	473.53	279.33	0.11	-0.07

Table 5.11: Performance Comparison of Different Models Using Multiple Evaluation Metrics

that the proposed methodologies can significantly enhance network planning and optimization capabilities.

5.10.2 Experimental Results

We analyze the performance of ARIMA and GRU models through their prediction patterns and error metrics. Figure 5.15 shows the ARIMA model's performance, where the MSE values are 224228.1144 for original scale and 0.031 for normalized data. The plot reveals significant deviation between actual and predicted values, particularly after the 40th time step, where the model fails to capture the increasing trend in the throughput values.

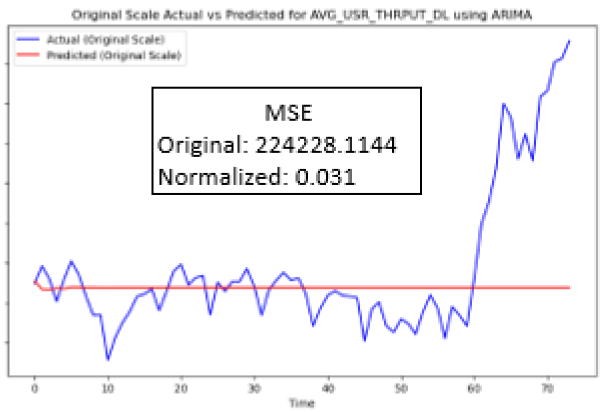

Figure 5.15: Comparison of Evaluation metric based on forecasting using ARIMA

Figure 5.16 presents the GRU model's predictions, showing MSE values of 118535.1155 for original scale and 0.0164 for normalized data. The GRU model demonstrates better alignment between actual and predicted values throughout the time series, including improved tracking of the trend after the 40th time step, though some deviations are still present.
While the MSE values might suggest large errors, particularly in the original scale, the R-squared metric in Table 5.11 provides a more nuanced evaluation. The GRU model achieves an R-squared value of 0.18, while ARIMA shows -0.07, indicating that GRU explains 18

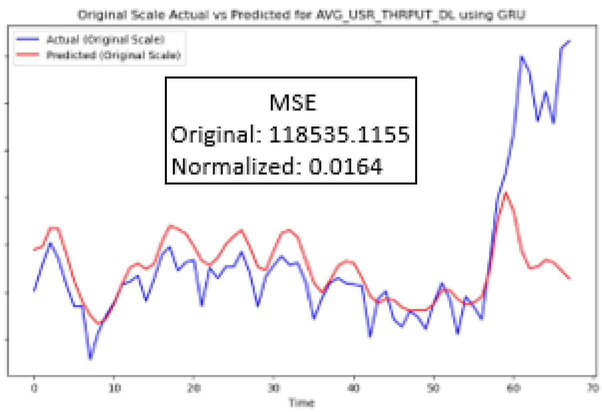

Figure 5.16: Comparison of Evaluation metric based on forecasting using GRU

5.10.3 Insights on Effective Evaluation Metrics

The analysis of various evaluation metrics provides crucial insights for both general forecasting applications and specific telecom network KPI forecasting scenarios. For general time series forecasting, R-squared emerges as a particularly valuable metric due to its scale-invariant nature and interpretability. Unlike MSE, which shows dramatically different values between normalized (0.0164) and original (118535.1155) scales for the GRU model, R-squared maintains consistent values regardless of data scaling. This property makes it especially useful for comparing models across different datasets and scales. In the context of telecom network KPI forecasting, where metrics can vary significantly in scale (from percentages to absolute throughput values), R-squared provides a standardized way to evaluate model performance. The negative R-squared value for ARIMA (-0.07) clearly indicates its inadequacy for the telecom KPI forecasting task, while the positive value for GRU (0.18) suggests its better suitability, even though there is still room for improvement. This interpretation is particularly valuable for network operators who need to compare models across different KPIs with varying scales and units. However, a comprehensive evaluation should still consider multiple metrics, as R-squared alone might not capture all aspects of model performance, such as the accuracy of peak throughput predictions which could be critical for network capacity planning.

5.11 Summary of Experiment

This chapter presents a comprehensive framework for optimizing time series forecasting in telecommunications networks through systematic analysis of multiple critical aspects. Through extensive experimentation and analysis, our research demonstrates several key findings that significantly advance our understanding of telecom network forecasting methodologies. The analysis of dataset selection reveals the superiority of area-level forecasting, with consistently lower MSE values compared to cell and site-level predictions. This finding challenges the conventional approach of focusing on granular data, suggesting that broader geographical aggregation provides more stable and reliable forecasting baselines. In the realm of data preprocessing, our study of normalization techniques establishes Min-Max scaling as the optimal choice, achieving an R-squared value of 0.93, significantly outperforming other normalization methods.

In the evaluation of model architectures, deep learning approaches, particularly GRU and LSTM variants, demonstrate superior performance across multiple KPIs. The hybridization of models yields particularly promising results, with the Hierarchical-LSTM achieving an R-squared value of 0.96, representing state-of-the-art performance in network KPI prediction. The incorporation of weekly seasonality patterns shows significant improvements, especially for user metrics with a 15.50% improvement and throughput with a 7.52% improvement, highlighting the importance of temporal pattern recognition in forecast accuracy. Our analysis of feature selection through real-world scenarios emphasizes the primacy of network performance metrics, particularly throughput, over device-specific considerations. This finding has direct implications for network operators' approach to service quality optimization.

The systematic investigation of hyperparameter tuning demonstrates the potential for substantial performance improvements, achieving up to 567% enhancement in R-squared values through careful optimization. These findings collectively contribute to a robust methodology for telecom network forecasting, emphasizing the critical importance of area-level data aggregation, appropriate normalization techniques, deep learning architectures with seasonal awareness, throughput-focused KPI selection, and systematic hyperparameter optimization. The research provides network operators with clear guidelines for implementing effective forecasting systems while balancing accuracy with practical considerations. The demonstrated improvements in prediction accuracy across various metrics and scenarios suggest that the proposed methodologies can significantly enhance network planning and optimization capabilities. Looking forward, future research directions could explore the integration of additional external factors and the development of more sophisticated hybrid architectures to further enhance prediction accuracy in telecom network forecasting applications.

Chapter 6

Results and Performance Evaluation

Network KPI forecasting requires careful consideration of multiple methodological aspects to achieve optimal performance. This analysis presents evidence-based findings from comprehensive experimentation across different modeling approaches, data processing techniques, and architectural decisions. Through systematic evaluation of these elements, we establish clear guidelines for implementing effective forecasting systems in telecommunications networks.

6.1 Dataset Selection for Network Performance Forecasting

Our analysis of network performance data demonstrates that area-level data consistently outperforms cell or site-level aggregations for general forecasting purposes. Through rigorous evaluation using multiple modeling approaches, including ARIMA, LSTM, GRU, SVM, and GRU-SVM hybrid models, area-level predictions achieved significantly lower Mean Squared Error values across all key performance indicators, suggesting superior predictive capabilities at this level of aggregation.

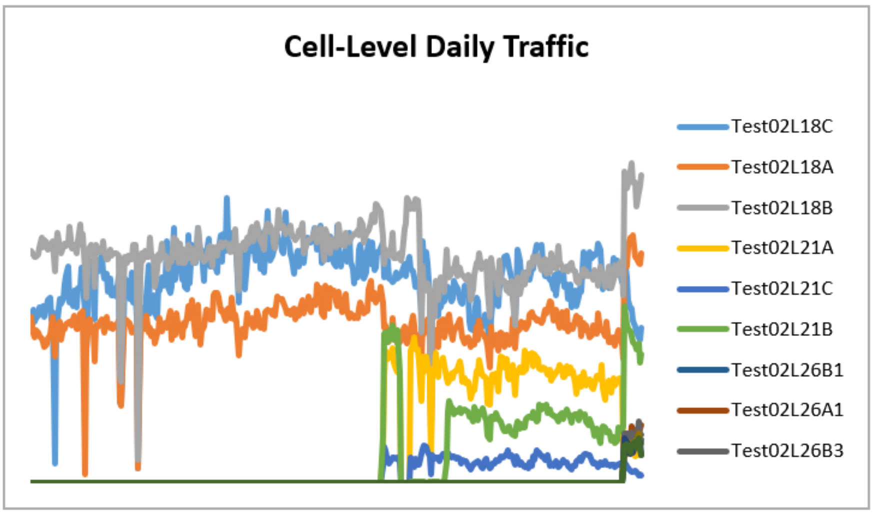

Figure 6.1: Cell-Level Daily Traffic

The effectiveness of area-level data lies in its fundamental ability to smooth out localized fluctuations that often complicate forecasting at more granular levels. As evidenced in Figure 6.1, individual cells exhibit considerable variability in their traffic patterns, presenting a significant challenge for accurate predictions. This cellular-level volatility, while important for operational insights, introduces complexity that can obscure broader network trends.

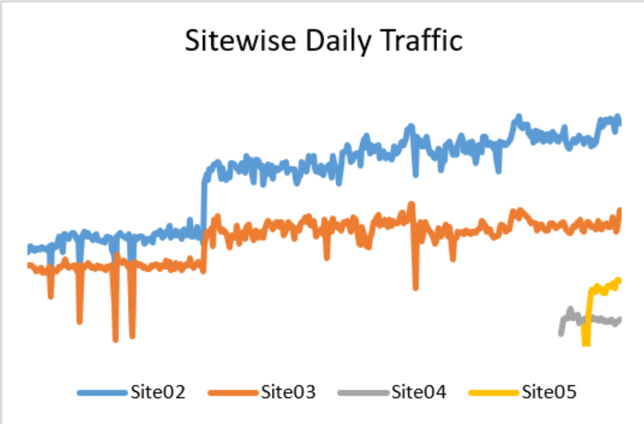

Figure 6.2: Site-wise Daily Traffic

At the site level, as depicted in Figure 6.2, traffic patterns begin to show more structure, though still retaining significant variability. This intermediate level of aggregation provides valuable insights into local network behavior while partially smoothing out the extreme fluctuations observed at the cellular level.

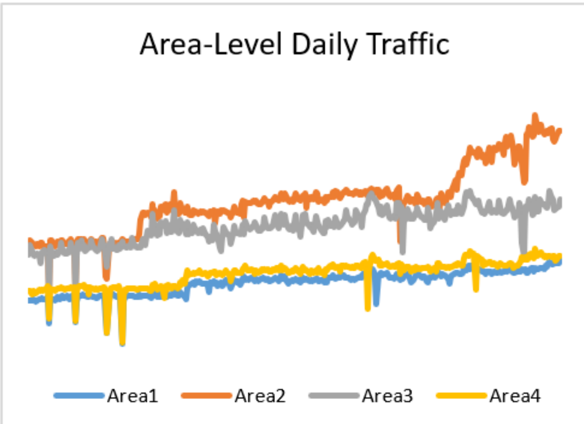

Figure 6.3: Area-Level Daily Traffic

Moving to the area level, Figure 6.3 reveals how traffic patterns stabilize significantly, maintaining steady growth momentum even when individual components experience fluctuations. This stability persists even when adjacent areas experience traffic increases, demonstrating the robustness of area-level aggregation. The reduced complexity in modeling area-level data, which consolidates multiple time series into a more manageable dataset, enhances forecast reliability and provides a comprehensive view for strategic planning purposes.
Table 6.1 highlights the superior performance of area-level data in traffic prediction. For instance, the R-squared values for SVM, GRU, and LSTM models are

Table 6.1: Comparison of R-Squared Value for Traffic Prediction

Model	**Cell**	**Site**	**Area**
SVM	0.5857	0.6480	0.9473
GRU	0.5957	0.7598	0.8573
LSTM	0.5957	0.7544	0.8791

significantly higher at the area level compared to cell and site levels. This further emphasizes the effectiveness of using area-level data for prediction, as it provides more reliable and accurate forecasts. The higher R-squared values indicate that the models explain a larger proportion of the variance in the data, leading to better predictive performance. This insight underscores the importance of leveraging area-level data for strategic forecasting in telecommunications networks.

This hierarchical analysis strongly supports the use of area-level data for strategic planning and forecasting purposes. The progressive stability from cell to area level demonstrates how data aggregation can reveal underlying patterns that remain obscured in more granular analyses. Our findings indicate that area-level data consistently outperforms cell or site-level data, achieving superior predictive accuracy across various models, including SVM, GRU, and LSTM. The effectiveness of expert-driven feature selection, proper normalization techniques, balanced data splitting ratios, and advanced forecasting architectures further enhances the reliability of area-level predictions. Additionally, incorporating weekly seasonality and carefully selecting correlated variants contribute to more accurate forecasts. The significant improvements achieved through systematic hyper-parameter tuning and the consistent reliability of R-squared values as an evaluation metric underscore the robustness of our methodology. This insight proves particularly valuable for network planning and resource allocation decisions, where stable, predictable patterns are essential for effective long-term strategy development.

6.2 Feature Selection Analysis for Network Quality Prediction

Our comprehensive study examining the relationship between device quality and network performance reveals critical insights that reshape our understanding of feature selection in network quality prediction. The analysis, contrasting a premium device (iPhone) experiencing poor network coverage against an unknown brand phone with excellent coverage, demonstrates that network quality metrics consistently emerge as the most reliable predictors of service performance, as illustrated in Figure 6.4. The experimental data presents a compelling narrative: network throughput and signal strength fundamentally determine service quality, consistently outweighing device capabilities in importance. In conditions of poor network coverage, even premium devices struggle with basic functionalities - producing blurry media, experiencing call distortions, and suffering from poor data speeds. Conversely, devices from lesser-known brands achieve excellent performance across all metrics when supported by

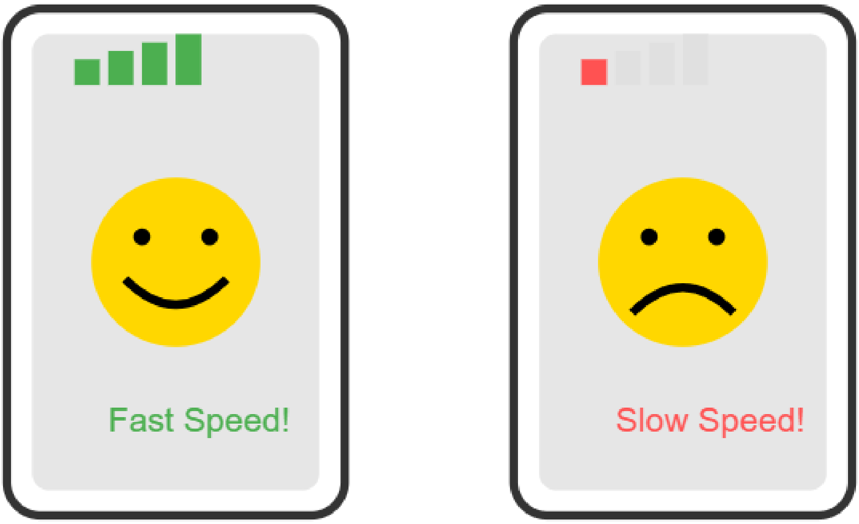

Figure 6.4: User Experience based on Network Throughput/speed

robust network coverage, as clearly demonstrated in Figure 6.4. This pattern holds true across various service aspects, from media sharing to voice calls, establishing network performance metrics as the definitive indicators of user experience quality.

Our findings suggest that network operators should fundamentally reshape their approach to prediction modeling. The evidence strongly supports prioritizing throughput-centric features and network performance indicators over device-specific considerations or basic traffic parameters. This shift in focus enables more accurate forecasting and proactive service quality management, as throughput demonstrates consistent correlation with user satisfaction across all service dimensions.

The visual evidence in our comparative analysis, particularly the stark contrast in user experience between different network conditions shown in Figure 6.4, provides compelling validation for these conclusions. The consistent pattern observed across different service aspects validates the technical consensus that throughput serves as the most reliable predictor of network service quality. For telecom operators, this insight fundamentally transforms the approach to feature selection in prediction models, emphasizing the critical importance of network performance metrics over traditional parameters.

This research contributes significant value to the field by demonstrating that features related to customer satisfaction and network performance, such as data speed and throughput, yield more accurate predictions than basic traffic metrics. The analysis reveals that these features are more directly correlated with the quality of user experience and network performance, making them invaluable for building robust prediction models in telecommunications networks.

6.3 Analysis of Data Normalization Techniques

Data normalization significantly impacts model performance in network KPI forecasting. As shown in Figure 6.5, Min-Max Scaling demonstrates superior performance with an R-squared value approaching 0.9, significantly outperforming other normalization techniques. Robust Scaling emerges as the second most effective approach, while Unit Vector normalization proves least suitable for network KPI forecasting applications. This evidence strongly supports the implementation of Min-Max Scaling as the standard normalization approach in network forecasting systems.

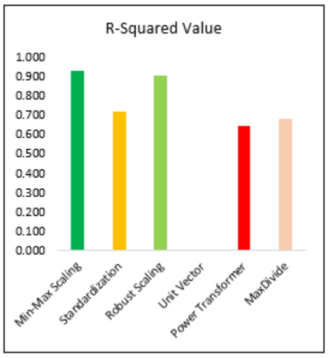

Figure 6.5: Comparison of R-squared values across different normalization techniques

6.4 Training Data Distribution Analysis

The allocation of training data significantly influences model performance. Figure 6.6 illustrates the relationship between training data percentage and model performance. The analysis reveals optimal performance in the 30-70% range, with peak R-squared values observed between 40-60% training data allocation. Notably, performance degradation occurs at both extremes (20% and 90% training splits), challenging traditional assumptions about larger training sets necessarily yielding better results.

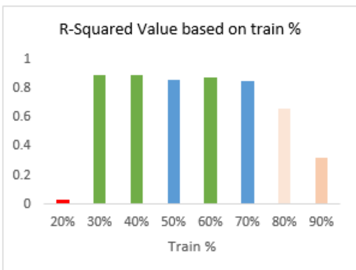

Figure 6.6: R-squared values based on training data percentage

6.5 Model Performance Evaluation

Comparative analysis of model performance across different metrics reveals varying effectiveness of different architectures. Figure 6.7 presents both MSE and R-squared comparisons across different models for User (Usr), Throughput (TP), and Traffic predictions. The results demonstrate superior performance of GRU and LSTM models across most metrics, while ARIMA consistently underperforms, particularly in traffic predictions where it shows negative R-squared values. This pattern strongly supports the adoption of advanced neural network architectures over traditional statistical approaches.

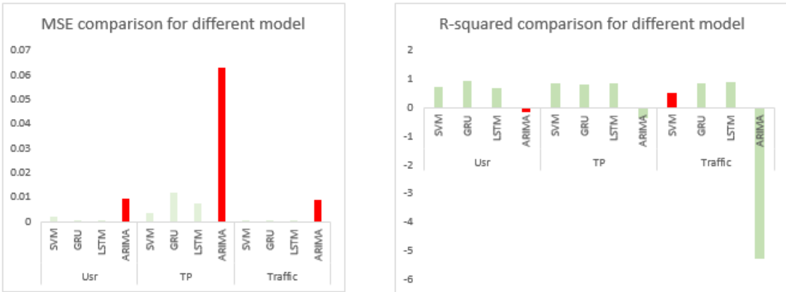

Figure 6.7: MSE and R-squared comparison across different models and metrics

6.6 Combined Model Architecture Analysis

Analysis of combined model architectures reveals significant variations in performance across different configurations. Figure 6.8 presents the R-squared values for various model combinations and architectures. The hierarchical-LSTM configuration demonstrates superior performance with an R-squared value approaching 0.96, followed closely by self-attention based models. Notably, the stacked and hybrid architectures generally outperform simpler combinations, with two-layer configurations showing particularly strong results. The GRU-SVM and LSTM-ARIMA combinations exhibit lower effectiveness, suggesting limited value in combining traditional statistical approaches with neural networks.

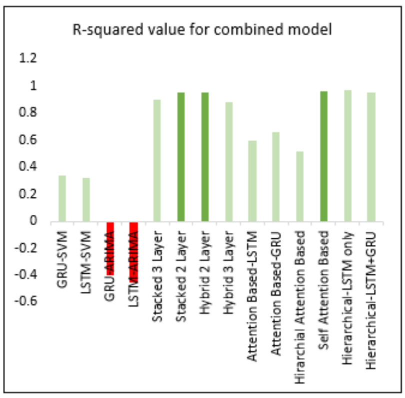

Figure 6.8: R-squared values for combined model architectures

6.7 Impact of Seasonality Patterns

The incorporation of seasonality patterns demonstrates varying effectiveness across different network elements. Figure 6.9 illustrates the impact of different seasonality patterns on model performance. Weekly seasonality patterns show consistent improvement across all metrics, with particularly strong impact on User and Throughput predictions. The R-squared values for weekly patterns consistently outperform both no-seasonality and monthly patterns, suggesting the dominance of weekly cycles in network usage patterns.

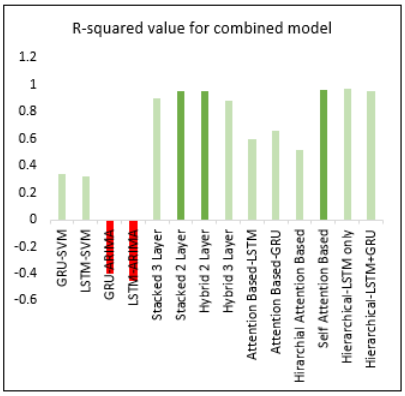

Figure 6.9: R-squared values for different seasonality patterns across metrics

6.8 Impact of Model Variants

Our analysis demonstrates that variant correlation strength significantly influences model performance across different network metrics. As illustrated in Figure 6.10, variants with high correlation coefficients generally enhance model accuracy, while those with lower correlations can substantially degrade performance. The relation-

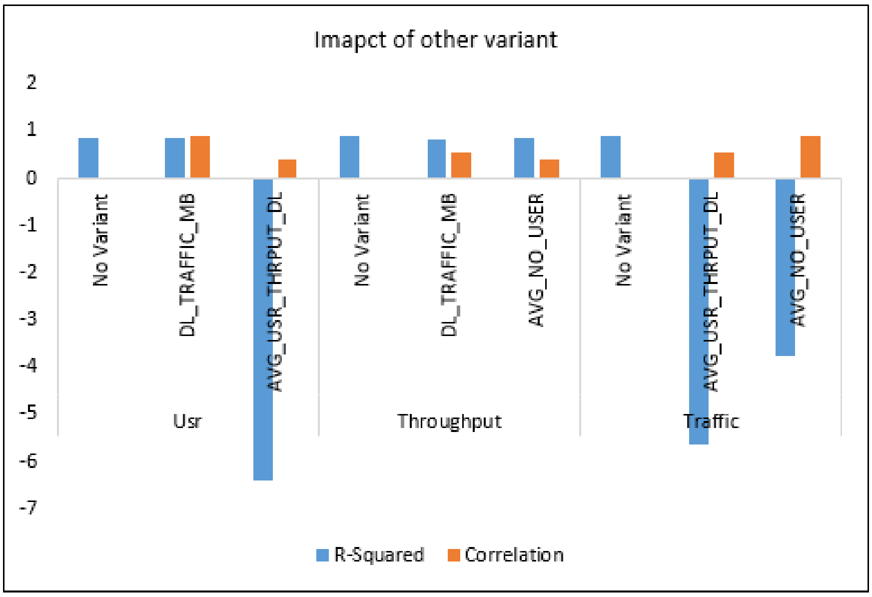

Figure 6.10: R-Squared Values for Different Variants Across Network Metrics

ship between correlation strength and model performance is particularly evident in the User prediction metrics. The DL_TRAFFIC_MB variant, exhibiting a strong correlation coefficient of 0.8993, improves the model's R-squared value from 0.8565 to 0.8792. Conversely, the AVG_USR_THRPUT_DL variant, despite showing a moderate correlation of 0.4127, significantly diminishes model performance, resulting in a negative R-squared value of -6.3848.

Throughput predictions further substantiate this pattern, where the baseline model achieves an R-squared value of 0.8895. Variants with moderate correlations (0.5668 for DL_TRAFFIC_MB and 0.4127 for AVG_NO_USER) show slightly reduced performance, yielding R-squared values of 0.8222 and 0.8544 respectively. The Traffic predictions notably emphasize that correlation strength must be considered alongside practical model performance, as variants with correlations of 0.5668 and 0.8993 result in negative R-squared values of -5.6304 and -3.7480.

These findings suggest that optimal forecasting model development requires careful feature selection based on correlation strength and validated performance improvements. The integration of highly correlated features should be preceded by rigorous testing to ensure they enhance rather than degrade predictive accuracy. This methodological approach helps maintain model robustness while leveraging the additional predictive power of well-chosen variants.

6.9 Impact of hyper-parameter Optimization

Our comprehensive analysis of hyper-parameter optimization reveals that systematic tuning significantly enhances model performance, with MSE improving by 265% and R-squared values showing substantial gains. The optimization process demonstrated remarkable improvements, as evidenced by the increase in R-squared value from 0.11 to 0.76, calculating to a 567% improvement:

$$\text{Improvement} = \left(\frac{0.76 - 0.11}{0.11}\right) \times 100 = 567\%$$

The significance of hyper-parameter tuning is further emphasized through our exploration of a comprehensive parameter space. Our investigation covered key parameters including Units (50, 100, 150), Dropout Rate (0.2, 0.3, 0.4), Batch Size (32, 64), Epochs (50, 100, 150), and Optimizer options (Adam, RMSprop). This systematic approach explored a theoretical search space of:

$$\begin{aligned}
&3 \text{ (Units)} \times 3 \text{ (Dropout Rate)} \times \\
&2 \text{ (Batch Size)} \times 3 \text{ (Epochs)} \times \\
&2 \text{ (Optimizer)} = 108 \text{ possible hyper-parameter combinations.}
\end{aligned}$$

Through strategic exploration of these combinations, focusing on promising parameter ranges guided by initial performance indicators and domain expertise, we achieved optimal model performance. This methodical approach to hyper-parameter tuning demonstrates that careful optimization of model parameters is crucial for maximizing predictive accuracy and overall model effectiveness. The results emphasize the importance of thorough hyper-parameter tuning in developing robust and accurate forecasting models.

6.10 Comparison of Evaluation Metrics in Model Performance

Our comprehensive analysis of evaluation metrics reveals that R-squared values emerge as the most reliable indicator for measuring model accuracy across different scenarios. Through extensive testing comparing normalized and original data, we found that while metrics like MSE, MAE, and RMSE show significant variations between scaled and unscaled data, R-squared values maintain remarkable consistency. For instance, in our GRU model implementation, the R-squared values remained steady at 0.18 for both normalized and original data, demonstrating its scale-invariant nature. Figure 6.11 shows evaluation of ARIMA and GRU models for justification of R-Squared as a Reliable Metric.

The significance of R-squared's stability becomes particularly apparent when examining model behavior across different scales. When evaluating the LSTM model, we observed that while the MSE varied dramatically between normalized (0.01) and original (99559.02) scales, the R-squared value held constant at 0.31. This consistency proves invaluable for comparing model performance across diverse datasets and scales, providing a standardized measure of model effectiveness.
Furthermore, our analysis demonstrates that R-squared's effectiveness extends beyond mere scale independence. The metric effectively captures the proportion of variance explained in the dependent variable (AVG_USR_THRPUT_DL), offering meaningful insights into model performance. In our comparative study between GRU and ARIMA models, R-squared values clearly identified GRU's superior performance, aligning with other performance indicators while maintaining scale independence.

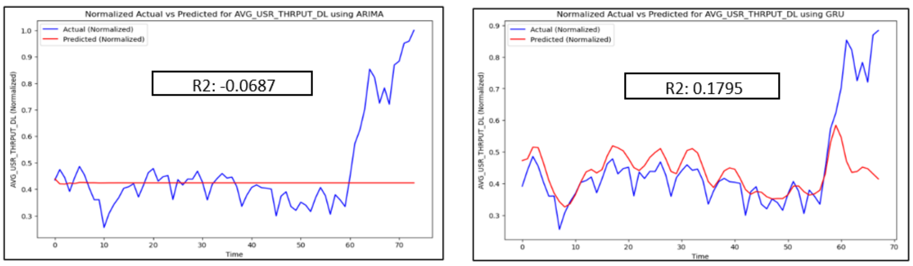

Figure 6.11: R-Squared as a Reliable Metric: Evaluating ARIMA and GRU Forecasting Models

This robust evidence supports the adoption of R-squared as the primary metric for evaluating forecasting models. By focusing on R-squared values, practitioners can make more reliable comparisons across different models, datasets, and scales, ensuring consistent and meaningful evaluation of model performance. This methodological approach provides a solid foundation for model selection and optimization, particularly in scenarios involving multiple scales or varying data distributions.

6.11 Experimental Results Summary

Table 6.2 summarizes the experimental results for each key finding:

Table 6.2: Summary of Experimental Results

Feature	**Result**	**Guideline**
Dataset Selection	Area-level data outperforms cell/site-level data	Use area-level data for strategic planning
Feature Selection	Expert-driven feature selection improves prediction reliability	Focus on network quality metrics
Normalization Techniques	Proper normalization improves model performance by up to 44%	Use Min-Max Scaling, consider Robust Scaling for outliers
Data Splitting Ratios	Training ratios between 30%-70% provide better accuracy	Aim for a balanced split
Model Performance	LSTM and GRU outperform ARIMA	Use LSTM and GRU models, consider hybrid models
Advanced Fused Models	Stacked and self-attenuation models achieve over 90% accuracy	Implement advanced architectures
Seasonality Patterns	Weekly seasonality improves accuracy by up to 15.50%	Incorporate weekly seasonality
Correlated Variants	Highly correlated variants enhance accuracy, less correlated degrade	Select and integrate highly correlated features
Hyper-parameter Tuning	Improves MSE by 265% and R-squared values significantly	Conduct thorough hyper-parameter tuning
Evaluation Metrics	R-squared values are the most reliable metric	Use R-squared values as the primary metric

These experimental results and guidelines collectively contribute to a robust methodology for telecom network forecasting, emphasizing the critical importance of area-level data aggregation, appropriate normalization techniques, advanced model architectures, and systematic hyper-parameter optimization. The research provides network operators with clear guidelines for implementing effective forecasting systems while balancing accuracy with practical considerations. The demonstrated improvements in prediction accuracy across various metrics and scenarios suggest that the proposed methodologies can significantly enhance network planning and optimization capabilities.

Chapter 7

Conclusion

This research has made significant strides in addressing the critical need for a unified approach to telecommunications forecasting, offering both theoretical advancements and practical implementations that bridge the gap between research and industry application. Through systematic investigation and comprehensive experimentation, we have established a robust framework that encompasses the entire forecasting life-cycle while addressing industry-specific challenges.

Our findings demonstrate that area-level forecasting consistently outperforms cell and site-level predictions, with experiments showing that modifications in data normalization techniques alone can improve model performance by up to 44%. The research establishes that weekly seasonality patterns provide superior results compared to monthly patterns, achieving improvements of 1.73%, 7.52%, and 15.50% for traffic, throughput, and user count respectively. This insight provides clear direction for practical implementation in telecommunications networks.

The framework's effectiveness is particularly evident in its ability to balance accuracy with operational efficiency. The integration of expert domain knowledge with advanced modeling techniques has yielded a standardized approach that not only improves prediction accuracy but also ensures data privacy—a critical consideration in telecommunications operations. Our systematic testing of data splits revealed that ratios between 30% to 70% consistently provide optimal accuracy for telecom network forecasting applications.

A key theoretical contribution lies in the framework's innovative synthesis of hierarchical data selection, temporal pattern recognition, and standardized evaluation methodologies. The research demonstrates that while statistical models like ARIMA prove inadequate for current telecom data patterns, LSTM and GRU architectures show superior performance. Most significantly, combined models achieve exceptional results, exceeding 90% accuracy in telecom network forecasting.

The practical implications of this research are substantial. By establishing clear guidelines for collaboration among stakeholders—including operators, vendors, service providers, and regulatory bodies—this framework provides a structured approach to forecasting that can adapt to evolving technological landscapes. Our findings on hyperparameter tuning, achieving a 265% improvement in MSE and elevating R-squared values from -60.8 to 0.76, offer concrete strategies for implementation.

However, the research also acknowledges certain limitations. While the framework excels in area-level forecasting, it provides more limited direction for cell and site-level predictions. This constraint reflects the inherent complexity of micro-level forecasting, where local factors and inter-dependencies create additional layers of complexity. Additionally, our focus on weekly and monthly seasonality patterns, while practical, means the framework provides limited guidance for other significant temporal patterns such as lunar cycles or holiday effects.

Looking forward, several promising research directions emerge. The framework could be extended to accommodate emerging technologies like 5G and IoT, expanding its applicability to new telecommunications paradigms. More comprehensive guidelines for cell and site-level predictions could be developed to address the current limitations in micro-level forecasting. The exploration of lunar and holiday seasonality patterns would enhance the framework's temporal analysis capabilities.

In conclusion, while acknowledging its limitations, this research provides a robust foundation for telecommunications forecasting that can be adapted and extended as technology and requirements evolve. The framework's success in combining theoretical rigor with practical applicability suggests that future developments in this direction will continue to enhance the telecommunications industry's ability to predict and prepare for evolving network demands. Through continued research and practical application, the limitations identified can be systematically addressed, further strengthening the framework's utility in telecommunications forecasting.
The findings and methodologies presented in this thesis not only advance our understanding of telecommunications forecasting but also provide a practical roadmap for implementation. As the telecommunications industry continues to evolve with the introduction of new technologies and changing user demands, the flexible and adaptable nature of this framework positions it as a valuable tool for future network planning and optimization efforts.

Future research avenues include extending the framework to accommodate emerging technologies such as 5G and IoT, exploring lunar and holiday seasonality patterns, and investigating applications beyond the telecommunications sector. By establishing clear guidelines for collaboration among stakeholders—including operators, vendors, service providers, and regulatory bodies—this research contributes to the development of robust forecasting practices that are aligned with the rapidly evolving technological landscape of the telecommunications industry.

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