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Predictive Analytics Models for Network Traffic Optimization in Distributed Enterprise Environments

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Abstract

This study examined the effectiveness of predictive analytics models for network traffic optimization in distributed enterprise environments, with particular emphasis on forecasting accuracy, computational performance, dynamic resource allocation, congestion reduction, latency, throughput, and bandwidth utilization. A quantitative experimental design was employed using 120,000 valid network traffic observations retained from an initial dataset of 128,640 records, representing a 93.28% retention rate after preprocessing. The final dataset was chronologically divided into 70% training, 15% validation, and 15% testing subsets, with 18,000 observations reserved for independent model evaluation. Six predictive approaches—Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), Random Forest, XGBoost, Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM)—were evaluated using MAE, MSE, RMSE, MAPE, R^2, training time, and inference time. LSTM demonstrated the strongest forecasting performance, achieving an MAE of 21.84 Mbps, RMSE of 28.50 Mbps, MAPE of 3.91%, and R^2 of 0.958, followed by GRU with an RMSE of 30.42 Mbps and R^2 of 0.952. Relative to ARIMA, LSTM reduced MAE by 43.21% and RMSE by 43.94%. Predictive traffic management also produced substantial operational improvements compared with non-predictive management. Bandwidth utilization increased from 67.84% to 76.92%, throughput increased by 16.09%, and resource-allocation efficiency improved by 18.09%. End-to-end latency decreased by 24.70%, packet loss declined by 36.36%, congestion frequency decreased by 37.05%, and congestion duration was reduced by 34.07%. Prediction error was significantly associated with congestion frequency ($r = 0.61$, $p < 0.001$) and negatively associated with resource-allocation efficiency ($r = -0.63$, $p < 0.001$). Significant effects were also identified for predictive model type, traffic-load intensity, and forecasting horizon. The findings demonstrated that predictive analytics, particularly recurrent deep learning models, provided measurable improvements in traffic forecasting and network optimization while highlighting the importance of balancing predictive accuracy, computational efficiency, workload intensity, and forecasting horizon in distributed enterprise network management.

Keywords

Predictive Analytics, Network Traffic, LSTM, Network Optimization, Enterprise Networks.

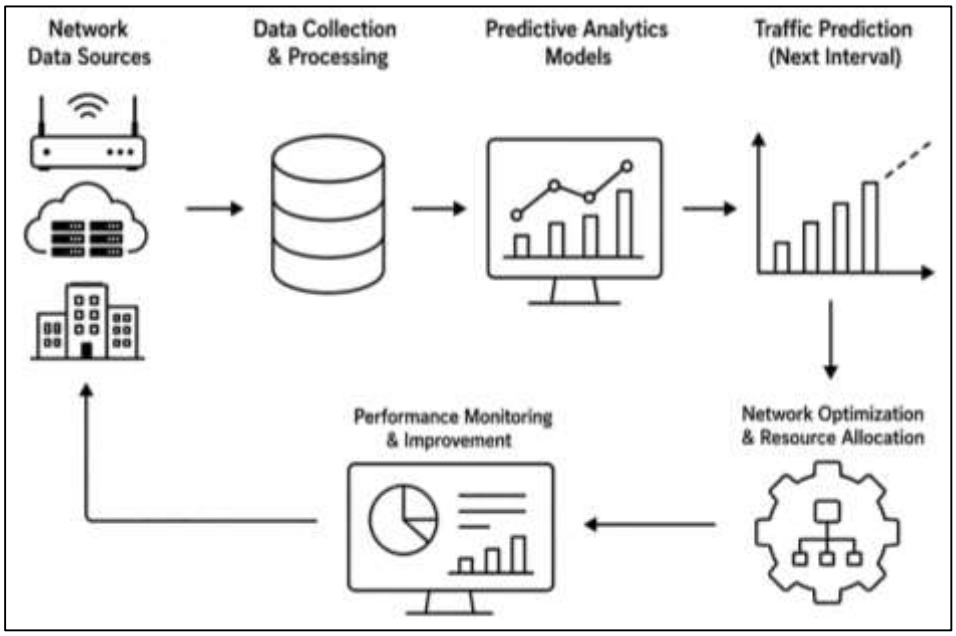
INTRODUCTION

Predictive analytics refers to the systematic application of statistical modeling, machine learning algorithms, data mining techniques, and computational methods to historical and real-time data for the purpose of estimating probable outcomes, identifying recurring patterns, and supporting data-informed operational decisions. Within computer networking, predictive analytics models are designed to learn from network traffic characteristics and estimate forthcoming traffic volumes, congestion states, bandwidth requirements, packet flows, latency conditions, application demands, and potential service disruptions (Adeleke, 2019). Network traffic can be defined as the volume, rate, direction, composition, and temporal distribution of data packets transmitted across interconnected computing and communication infrastructures. Network traffic optimization, in turn, represents the coordinated process of allocating network resources, managing routing decisions, regulating data flows, balancing workloads, reducing congestion, and maintaining acceptable levels of throughput, latency, packet delivery, and service availability. These concepts become particularly important in distributed enterprise environments, which consist of geographically dispersed organizational computing resources connected through local-area networks, wide-area networks, cloud infrastructures, data centers, branch offices, edge systems, virtualized environments, and internet-based communication platforms (Sone et al., 2021). Distributed enterprises generate heterogeneous traffic patterns because organizational users, applications, databases, Internet of Things devices, cloud services, enterprise resource planning systems, customer relationship management applications, videoconferencing platforms, and digital collaboration systems continuously exchange information across different network segments. Traditional reactive network management approaches commonly allocate resources or respond to congestion after performance degradation has already been observed, whereas predictive analytics provides a data-oriented mechanism for estimating network conditions before resource-management decisions are executed. The quantitative character of predictive analytics is especially relevant because traffic conditions can be represented through measurable variables such as bandwidth utilization, packet arrival rate, flow duration, round-trip time, jitter, packet loss, queue length, link utilization, throughput, response time, and network availability. Predictive models can consequently establish statistical or computational relationships between historical traffic observations and measurable network-performance outcomes (Sone et al., 2020). In distributed enterprise contexts, these relationships are rarely uniform because traffic characteristics vary across locations, time periods, applications, network architectures, organizational workloads, and user populations. Predictive network optimization therefore involves both forecasting and decision support, connecting estimates of traffic behavior with resource-allocation mechanisms intended to maintain network performance. This conceptual relationship positions predictive analytics as a measurable approach to understanding how network demand develops across complex enterprise infrastructures and provides the analytical foundation for quantitatively examining the association between prediction accuracy, resource utilization, congestion reduction, throughput, latency, packet loss, and overall network efficiency (Troia et al., 2018).

The increasing complexity of enterprise networks has strengthened the importance of quantitative methods capable of identifying traffic patterns that conventional rule-based network management mechanisms may not adequately represent. Earlier network traffic management systems largely depended on predetermined routing rules, static bandwidth allocation, threshold-based monitoring, and administrator-defined policies. These mechanisms remain important components of network administration, yet the expansion of cloud computing, virtualization, software-defined networking, mobile connectivity, edge computing, and Internet of Things deployments has created traffic environments characterized by substantial variability and multidimensional relationships. Predictive analytics extends network management beyond descriptive monitoring by transforming accumulated traffic measurements into estimates of subsequent network conditions (Bi et al., 2021). Statistical time-series techniques such as autoregressive models, moving-average models, autoregressive integrated moving average models, exponential smoothing, and regression analysis have been applied to network traffic forecasting because temporal traffic observations frequently contain trends, periodicity, autocorrelation, and short-term dependencies. Machine learning approaches have broadened this analytical capacity by enabling relationships to be estimated from larger sets of traffic variables without

requiring all functional associations to be specified in advance. Support vector regression, decision trees, random forests, gradient-boosting methods, artificial neural networks, clustering techniques, and ensemble learning models have consequently become relevant to traffic prediction and classification (Zhang et al., 2020).

Figure 1: Predictive Analytics for Network Optimization



Deep learning methods, including recurrent neural networks, long short-term memory networks, gated recurrent units, convolutional neural networks, autoencoders, graph-based models, and hybrid architectures, provide additional mechanisms for representing nonlinear, spatial, and temporal dependencies in network data. The value of these models in distributed enterprise environments is connected to the diversity of traffic generated across interconnected organizational systems. A single enterprise network may simultaneously transport transactional database traffic, voice communications, video streams, cloud application requests, cybersecurity telemetry, file transfers, remote desktop sessions, automated backups, and machine-to-machine communications. Each category can exhibit different bandwidth, latency, reliability, and temporal characteristics, making aggregate traffic management quantitatively demanding. Predictive modeling provides a mechanism for estimating these heterogeneous patterns through historical observations and measurable explanatory variables (Hwang et al., 2019). Model effectiveness, however, depends on elements such as data quality, feature selection, sampling frequency, training procedures, model architecture, computational requirements, and the stability of traffic relationships across network locations. Quantitative evaluation is therefore central to determining whether a predictive model meaningfully contributes to optimization. Measures such as mean absolute error, root mean square error, mean absolute percentage error, coefficient of determination, prediction latency, computational overhead, throughput improvement, bandwidth utilization, congestion frequency, and packet-loss reduction permit researchers to compare analytical performance systematically. The transition toward data-driven traffic modeling has consequently transformed network optimization into an empirical problem in which prediction quality and operational network outcomes can be measured jointly.

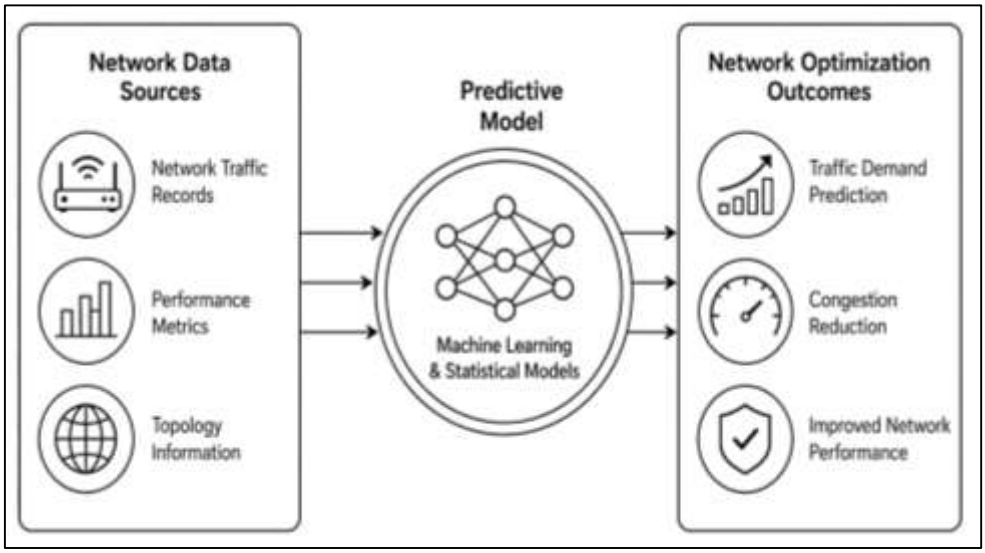
Distributed enterprise environments constitute a particularly significant setting for predictive network traffic optimization because organizational information resources are increasingly distributed across multiple physical and virtual locations (Zhang et al., 2021). An enterprise may maintain corporate headquarters, regional branches, remote offices, private data centers, public-cloud workloads, software-as-a-service platforms, edge computing nodes, mobile workforces, virtual private networks, and interconnected operational technologies within the same broader information ecosystem. The

resulting network does not function as a single homogeneous communication channel; rather, it represents a collection of interconnected network domains with different capacities, protocols, service requirements, security controls, workloads, and geographical characteristics. Traffic generated in one domain can influence resource utilization and service quality in another, particularly when applications depend on centralized databases, cloud services, shared storage systems, authentication platforms, or cross-regional processing resources. Geographic distance also introduces measurable latency, while differences in available bandwidth and routing paths contribute to variations in transmission performance. Enterprise traffic can further demonstrate pronounced temporal fluctuations associated with working hours, transaction cycles, software updates, backup schedules, virtual meetings, customer activity, seasonal demand, and automated business processes (Lopez-Martin et al., 2017). These variations create a quantitative resource-allocation problem because network capacity must accommodate both routine demand and unexpected increases without producing excessive congestion or unnecessary overprovisioning. Predictive analytics models address this problem by estimating traffic demand at different network nodes, links, applications, and time intervals. The resulting forecasts can be integrated with traffic engineering mechanisms such as dynamic routing, load balancing, bandwidth allocation, queue management, path selection, quality-of-service controls, and software-defined networking policies. A model that accurately predicts an increase in traffic between enterprise locations can support earlier resource allocation or alternative path selection, while predictions of reduced demand can support more efficient distribution of available network capacity. The distributed nature of the environment also introduces challenges associated with data heterogeneity (Bakhareva et al., 2019). Traffic observations may originate from routers, switches, firewalls, network controllers, cloud-monitoring services, flow records, packet captures, application logs, and telemetry platforms, creating datasets with different levels of granularity and completeness. Predictive performance can vary according to whether models are trained using aggregated traffic volumes, flow-level characteristics, application-level metrics, topology information, or combinations of these variables. Network optimization therefore requires an empirical understanding of how predictive accuracy interacts with the structural complexity of enterprise infrastructures (Yue et al., 2021). Quantitative investigation provides a means of testing these relationships by measuring model outputs against actual network behavior and comparing operational performance across traffic conditions, organizational locations, and network segments. Distributed enterprise networking thus provides a suitable environment for evaluating predictive analytics as both a forecasting mechanism and an operational optimization instrument.

The international significance of predictive analytics for network traffic optimization is closely associated with the globalization of digital business operations and the increasing dependence of organizations on geographically distributed information infrastructures (Pham et al., 2021). Multinational corporations, financial institutions, universities, healthcare organizations, manufacturing enterprises, logistics providers, government agencies, technology companies, and international service organizations routinely exchange substantial volumes of digital information across national and regional boundaries. Enterprise applications hosted in one geographic region may serve employees, customers, suppliers, and organizational facilities located thousands of kilometers away, creating network conditions influenced by distance, infrastructure quality, connectivity arrangements, regulatory boundaries, and differences in regional demand. Global cloud computing has intensified this interconnectedness because enterprises increasingly distribute applications and data across multiple cloud regions and providers while maintaining connections to private infrastructure and local branch networks (Shi et al., 2020). International organizations consequently require networks that can support predictable application performance across diverse operating conditions. Traffic optimization becomes economically significant because network congestion, excessive latency, packet loss, inefficient routing, and inadequate bandwidth allocation can affect transaction processing, communication quality, cloud application responsiveness, digital collaboration, production coordination, and access to organizational information resources. Predictive analytics offers a quantitative method for identifying patterns within this geographically dispersed traffic and estimating changes in demand across interconnected network domains. International significance also arises from the uneven distribution of networking resources across countries and regions.

Organizations operating across markets with different broadband capacities, infrastructure maturity, data-center availability, and connectivity costs cannot necessarily rely on uniform resource-provisioning strategies (Zheng & Leivadeas, 2021).

Figure 2: Predictive Analytics for Network Optimization



Predictive models can provide estimates that account for location-specific traffic behavior and assist in allocating network resources according to observed demand. Global enterprises also operate across multiple time zones, producing traffic patterns that may shift geographically throughout the day as employees, customers, and digital services become active in different regions. Such patterns create spatial-temporal relationships that are particularly suitable for quantitative analysis. Predictive models capable of representing temporal dependencies and cross-location relationships can therefore be evaluated according to their ability to estimate traffic volumes and network-performance indicators across distributed regions. International digital transformation has additionally expanded the number of cloud-connected devices, remote workers, enterprise applications, and machine-generated communications participating in organizational networks. As these resources interact across international infrastructures, traffic management becomes an important component of business continuity and digital service delivery (Bi et al., 2022). Quantitative research on predictive network optimization consequently has relevance beyond a single organization or geographic market because it addresses measurable networking challenges shared by enterprises operating within increasingly interconnected global digital environments.

Predictive analytics for network traffic optimization is inherently suited to quantitative investigation because both predictive performance and network operational performance can be represented through observable and measurable variables (Hu et al., 2019). Network traffic datasets commonly include packet counts, byte volumes, flow rates, source and destination characteristics, protocol distributions, session duration, link utilization, queue occupancy, bandwidth consumption, packet interarrival times, and application-specific traffic measurements. These variables can function as predictors for estimating dependent measures such as subsequent traffic volume, congestion probability, link utilization, throughput, latency, packet loss, jitter, response time, or resource demand. The relationship between predictor variables and network outcomes can be examined through statistical modeling, supervised machine learning, deep learning, and comparative algorithmic evaluation. Forecasting accuracy represents one major dimension of model performance and can be measured through error metrics including mean absolute error, mean squared error, root mean square error, mean absolute percentage error, symmetric mean absolute percentage error, and related statistical indicators (Perry et al., 2018). Operational effectiveness constitutes a separate but interconnected dimension because a model with low forecasting error does not automatically produce

equivalent improvements in network performance unless its predictions are incorporated effectively into resource-management decisions. Quantitative analysis can therefore examine changes in bandwidth utilization, average end-to-end delay, packet delivery rate, throughput, congestion duration, load distribution, routing efficiency, and quality-of-service compliance following predictive optimization. Computational performance is also relevant because enterprise traffic decisions frequently occur under strict time constraints. Training time, inference latency, processor utilization, memory consumption, model complexity, and communication overhead can influence whether a predictive approach is operationally suitable for distributed environments. Scalability introduces another measurable consideration, as models may perform differently when the number of network nodes, users, flows, applications, or geographical locations increases (Jiang et al., 2022). Reliability of predictions across changing traffic conditions can be assessed through repeated observations, validation datasets, cross-validation procedures, or testing across distinct network segments. The quantitative framework also allows comparisons among predictive approaches, enabling researchers to determine whether observed differences in forecasting and optimization outcomes are statistically meaningful. Correlation analysis, regression modeling, analysis of variance, hypothesis testing, effect-size estimation, and other statistical procedures can be applied according to the research design and measurement structure. Through such measurements, predictive network optimization can be investigated as a set of testable relationships rather than as an exclusively conceptual or technical proposition (Muhuri et al., 2020). The integration of prediction metrics with network-performance indicators is particularly important because it establishes a measurable connection between analytical accuracy and operational network efficiency within distributed enterprise environments.

The relationship between predictive modeling and dynamic resource allocation represents a central dimension of network traffic optimization because enterprise networks must distribute finite communication resources among multiple applications, users, devices, and organizational locations. Bandwidth allocation, routing capacity, processing resources, queue priorities, and network paths are limited at any given moment, while traffic demand continuously changes according to organizational activity (Aceto et al., 2019). Predictive analytics models can estimate these changes from historical and current traffic measurements, providing quantitative information that can be incorporated into network control mechanisms. In software-defined networking environments, for example, centralized or logically centralized controllers can use predicted traffic conditions to adjust forwarding rules, redistribute flows, or select alternative network paths. In cloud-connected enterprise environments, predicted workload variations can support adjustments to virtual network resources, load balancers, application gateways, and interregional communication capacity. Similar predictive information can support quality-of-service management by identifying periods in which latency-sensitive applications such as voice, video, real-time collaboration, or transactional systems are likely to encounter increased competition for network resources. Dynamic allocation based on predicted demand can consequently be evaluated by measuring whether network resources are distributed more efficiently than under static or reactive approaches (Troia et al., 2020). Service quality provides an important operational dimension of this evaluation. Enterprise users interact with networks primarily through applications and digital services, meaning that network-level performance influences application response times, session stability, communication quality, and accessibility of organizational resources. High latency can reduce responsiveness, packet loss can interrupt real-time communication, excessive jitter can affect voice and video quality, and congestion can delay transactions or data transfers. Predictive optimization connects model estimates with these measurable service characteristics by attempting to allocate network capacity before demand exceeds acceptable operating levels. The strength of this relationship can vary according to forecasting horizon, model accuracy, traffic volatility, network topology, and the speed at which optimization mechanisms respond to predictions (Awan et al., 2021). Short forecasting horizons may provide highly current information while allowing limited time for resource adjustment, whereas longer horizons may provide greater preparation time while introducing greater uncertainty. Model evaluation must therefore account for both statistical accuracy and the operational timing of predictions. Distributed enterprise environments make this assessment particularly relevant because traffic flows frequently traverse multiple network segments under different administrative and technical conditions. Quantitative measurement of prediction error,

allocation efficiency, congestion levels, latency, throughput, and packet loss provides an empirical basis for determining how predictive modeling interacts with dynamic network control and enterprise service quality (Zhang et al., 2020).

The expanding application of predictive analytics to communication networks has generated a substantial body of research examining traffic forecasting, congestion prediction, routing optimization, bandwidth management, software-defined networking, machine learning, deep learning, and intelligent resource allocation. Across this body of scholarship, researchers have investigated statistical forecasting methods, conventional machine learning algorithms, neural-network architectures, reinforcement-learning mechanisms, and hybrid analytical approaches under a variety of network conditions. Existing studies collectively demonstrate that network traffic contains measurable temporal, spatial, and application-specific patterns that can be modeled using historical observations (Bodström & Hämäläinen, 2018). At the same time, the empirical literature presents considerable variation in datasets, network architectures, forecasting horizons, traffic characteristics, evaluation metrics, experimental configurations, and definitions of optimization performance. Some studies emphasize prediction accuracy without directly measuring the resulting changes in network efficiency, while others concentrate on routing or resource allocation without establishing a detailed quantitative relationship between forecast quality and enterprise-level performance indicators. Experimental research is also frequently conducted using public traffic datasets, simulations, data-center traces, cellular networks, or controlled software-defined networking environments (Giannopoulos et al., 2022). These settings provide valuable evidence for algorithmic performance, although distributed enterprise environments introduce a combination of geographic dispersion, heterogeneous applications, mixed infrastructure, variable bandwidth conditions, cloud connectivity, and organizational traffic cycles that requires focused quantitative examination. A quantitative study of predictive analytics models in this context can define independent, dependent, and control variables in measurable terms and evaluate relationships through empirical network observations. Predictive model characteristics, historical traffic measurements, forecasting horizons, and traffic features can be associated statistically with dependent outcomes such as prediction error, bandwidth utilization, throughput, latency, packet loss, congestion frequency, and resource-allocation efficiency. Comparative analysis can also determine whether differences among predictive models correspond to statistically significant differences in network outcomes under consistent experimental conditions (Ouyang et al., 2022). Establishing this empirical structure is important because predictive analytics involves two interconnected analytical questions: how accurately a model estimates network traffic and how effectively those estimates correspond with measurable optimization outcomes. Treating these dimensions jointly provides a stronger quantitative basis for examining predictive traffic management within complex enterprise infrastructures. The present research context therefore centers on systematic measurement, model comparison, statistical testing, and objective evaluation of network-performance variables across distributed enterprise environments, with particular attention to the relationship between predictive accuracy and operational optimization (Li et al., 2021). Such a research structure provides a defined empirical basis for assessing predictive analytics models across heterogeneous traffic conditions and distributed organizational network configurations.

The primary objective of this quantitative study is to evaluate the effectiveness of predictive analytics models in optimizing network traffic performance within distributed enterprise environments by establishing measurable relationships between predictive capabilities, network resource utilization, and key operational performance indicators. Specifically, the study seeks to examine how predictive analytics models can utilize historical and real-time network traffic data to accurately estimate traffic volumes, identify potential congestion conditions, anticipate bandwidth requirements, and support data-driven allocation of network resources across geographically and technologically distributed enterprise infrastructures. The research aims to quantitatively assess the predictive accuracy of selected statistical, machine learning, and deep learning models through established performance measures such as mean absolute error, mean squared error, root mean square error, mean absolute percentage error, and coefficient of determination. In addition, the study intends to determine the extent to which variations in prediction accuracy are associated with measurable improvements in network performance, particularly bandwidth utilization, throughput, end-to-end latency, packet loss,

congestion frequency, response time, and overall resource-allocation efficiency. Another objective is to compare the performance of selected predictive analytics models under heterogeneous enterprise traffic conditions involving different traffic volumes, application categories, network segments, workload intensities, and temporal patterns. The study also seeks to measure whether predictive traffic management provides statistically significant differences in network performance when compared with conventional reactive or non-predictive traffic-management approaches under comparable network conditions. Particular attention is directed toward evaluating the capacity of predictive models to support dynamic routing, load balancing, bandwidth allocation, and congestion management across distributed network nodes while maintaining acceptable levels of service quality. Furthermore, the research aims to examine the statistical relationships among traffic characteristics, predictive model outputs, and network optimization outcomes to identify the variables that most strongly explain variations in enterprise network performance. Through structured data collection, predictive modeling, comparative evaluation, and statistical testing, the study seeks to generate empirical evidence concerning the effectiveness, accuracy, computational efficiency, and operational performance of predictive analytics models in distributed enterprise networks. The objective therefore encompasses both the analytical performance of traffic prediction models and their measurable contribution to network optimization, establishing a quantitative framework through which predictive accuracy, traffic behavior, resource utilization, and network performance can be systematically assessed and compared across complex distributed enterprise environments.

LITERATURE REVIEW

The literature on predictive analytics for network traffic optimization encompasses an interdisciplinary body of knowledge connecting computer networking, statistical forecasting, machine learning, deep learning, software-defined networking, traffic engineering, and enterprise information infrastructure. Network traffic optimization has increasingly developed from reactive traffic-management mechanisms toward data-driven approaches capable of estimating traffic conditions and incorporating predicted network states into routing, bandwidth allocation, congestion management, and resource-control decisions (Bellavista et al., 2021; Kanti, 2020). Within distributed enterprise environments, this transition is particularly important because traffic is generated across geographically separated branch networks, data centers, cloud platforms, virtualized infrastructures, edge systems, remote users, and application environments that exhibit heterogeneous patterns of bandwidth consumption, latency sensitivity, and service demand. Predictive analytics provides a quantitative mechanism for analyzing historical and real-time network observations and estimating subsequent traffic volumes, bandwidth requirements, congestion states, packet-loss conditions, and other network-performance characteristics. Existing empirical studies have consequently investigated conventional statistical models, machine learning algorithms, recurrent neural networks, long short-term memory models, gated recurrent units, convolutional neural networks, ensemble techniques, and hybrid architectures for traffic prediction (Debasish, 2021; El-Sayed et al., 2017). Research has also expanded from prediction accuracy alone toward the integration of forecasting with network optimization, particularly within software-defined networking and dynamically controlled network architectures. Evidence from comparative research indicates that predictive performance can vary considerably across algorithms, datasets, network sizes, forecasting intervals, and traffic characteristics, emphasizing the importance of evaluating models under clearly specified quantitative conditions. Studies using large-scale flow data have demonstrated the relevance of machine learning for short-term bandwidth prediction, while LSTM-based approaches have been extensively investigated for traffic-matrix forecasting and temporal dependency modeling. More recent comparative work has examined LSTM, BiLSTM, GRU, and BiGRU models across datasets such as GÉANT, Abilene, and SDN traffic datasets, illustrating measurable differences in prediction error and inference time (Cheng et al., 2017; Abdur & Iftekhar, 2021). The literature therefore provides a substantial empirical foundation for examining how predictive accuracy is associated with actual network optimization outcomes. For a quantitative investigation, particular attention must be given to the operationalization of traffic characteristics, prediction accuracy, computational performance, bandwidth utilization, throughput, latency, packet loss, congestion, and resource-allocation efficiency. Accordingly, this literature review synthesizes previous research according to measurable relationships rather than discussing predictive technologies only

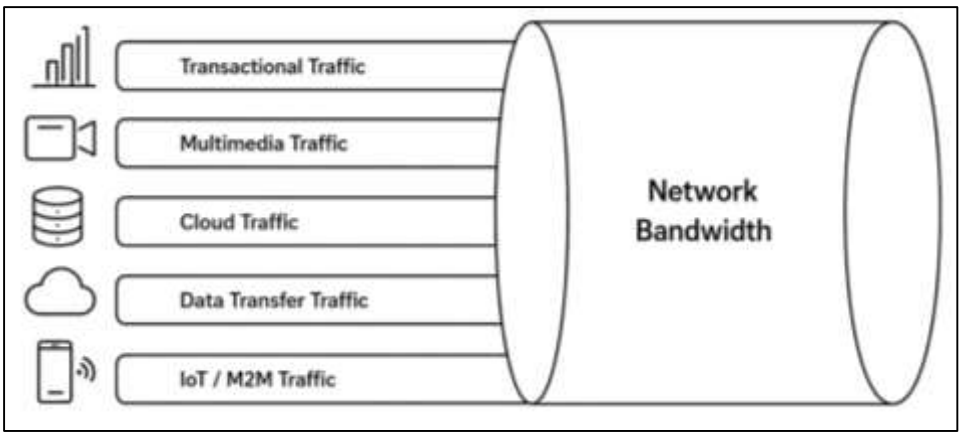
descriptively. The review is structured around network traffic characteristics, predictive-model categories, prediction-performance metrics, optimization mechanisms, enterprise network conditions, and empirical relationships between predictive analytics and network-performance outcomes (Chowdhury & Tonay, 2022; Naranjo et al., 2019).

Quantitative Characteristics of Network Traffic in Distributed Enterprise Environments

The quantitative characterization of network traffic in distributed enterprise environments begins with the measurement of traffic volume, packet transmission rates, flow intensity, and the temporal behavior of communication activities. Existing network measurement literature has established traffic volume as one of the principal indicators for determining the level of demand placed on communication infrastructure. Traffic volume can be expressed through bytes, packets, megabits per second, or gigabits per second, depending on network capacity, measurement objectives, and the level of traffic aggregation (Zahidul & Begum, 2022; Wang et al., 2015). Studies of enterprise, backbone, data-center, and wide-area networks have demonstrated that aggregate volume alone does not sufficiently characterize network workload because identical traffic volumes can emerge from substantially different packet and flow behaviors. Packet arrival rate and packet interarrival time provide more detailed representations of traffic intensity by capturing the frequency with which packets enter network links, routers, gateways, and processing queues. Research has associated high packet arrival rates and short interarrival periods with increased processing requirements and greater probability of queue accumulation under capacity constraints. Flow-level measurements complement packet-level observations by identifying concurrent communication sessions and quantifying their duration and size. Empirical studies have repeatedly documented substantial heterogeneity between short-lived flows carrying relatively small amounts of data and long-duration or high-volume flows consuming considerable network capacity (Nishat & Kaniz, 2022; Yan et al., 2015). The number of concurrent flows is therefore an important measure of network workload, particularly in distributed enterprises where thousands of simultaneous connections can originate from employees, applications, servers, cloud platforms, mobile devices, and automated systems. Another established characteristic is the distinction between peak and off-peak traffic intensity. Enterprise workloads commonly increase during working hours, scheduled processing periods, synchronization activities, backups, and periods of intensive application usage, while lower traffic levels occur during less active operating periods. Temporal aggregation intervals also influence the observed properties of network traffic. Measurements collected at very short intervals can reveal bursts and rapid fluctuations that become less visible when observations are aggregated across longer intervals (Darwish & Bakar, 2018). Consequently, quantitative traffic measurement requires simultaneous consideration of volume, packet rate, flow intensity, flow duration, flow size, time intervals, and location-specific variation to accurately represent workload conditions across distributed enterprise infrastructures.

Statistical analysis of enterprise network traffic provides an important foundation for understanding how communication demand varies over time and whether observed traffic patterns possess characteristics suitable for predictive modeling. A substantial body of network traffic research has examined mean traffic volume, variance, standard deviation, burstiness, peak-to-average behavior, autocorrelation, temporal dependence, periodicity, and nonstationarity. Mean traffic volume provides an aggregate representation of typical network demand during a specified observation period, while variance and standard deviation indicate the magnitude of fluctuations around that average (Bhushan & Gupta, 2019; Badrul & Mominul, 2023). These measures are particularly relevant to distributed enterprise networks because average utilization can conceal substantial short-duration increases capable of generating congestion and performance degradation. Research on internet and enterprise traffic has consistently identified burstiness as a fundamental traffic characteristic, with network demand frequently exhibiting rapid increases and decreases rather than uniform transmission behavior. Peak-to-average traffic relationships provide another quantitative perspective by indicating the extent to which maximum observed demand exceeds normal operating levels. Large differences between average and peak traffic create significant challenges for capacity management because infrastructure designed solely around average utilization may encounter resource limitations during periods of concentrated demand (Kanti, 2024; Yan & Yu, 2015).

Figure 3: Enterprise Network Traffic Characteristics Analysis



Temporal dependence further distinguishes network traffic from completely random sequences. Studies examining autocorrelation have shown that current traffic observations can maintain measurable relationships with previous observations across multiple time intervals, providing an empirical foundation for time-series forecasting and sequence-based machine learning approaches. Daily and weekly periodicities have also been documented across organizational and internet networks, reflecting recurring patterns associated with employee activity, customer transactions, application schedules, backup operations, and differences between working and non-working periods. At the same time, enterprise traffic frequently exhibits nonstationary characteristics because its statistical properties can change as workloads, user populations, applications, routing conditions, and organizational activities vary (Sivanathan et al., 2018; Tonay et al., 2024). Such changes can influence the performance of predictive models trained under earlier traffic distributions. The combined findings of statistical, networking, and machine learning studies therefore indicate that enterprise traffic should be represented through multiple descriptive and temporal characteristics rather than a single average measure. Examining dispersion, burst intensity, autocorrelation, periodicity, and changes in statistical distributions provides a more comprehensive quantitative representation of traffic behavior and supports the identification of meaningful variations across observation periods.

Spatial variation represents another major quantitative characteristic of network traffic because distributed enterprise infrastructures connect geographically separated branches, data centers, cloud platforms, regional facilities, remote users, and centralized organizational resources through heterogeneous communication paths (Murray et al., 2017). Empirical research on wide-area networks, traffic matrices, software-defined networks, cloud infrastructures, and geographically distributed systems has demonstrated that network demand is rarely distributed uniformly across nodes or links. Branch-to-branch traffic varies according to organizational size, workforce activity, application usage, business functions, geographical location, and dependence on centralized information systems. A regional office supporting large numbers of employees or transaction-intensive operations can generate substantially greater traffic than a smaller branch performing limited functions. Data-center traffic presents additional spatial characteristics because communication can occur between servers within the same facility, between data centers, or between data centers and external enterprise locations (Kwahk & Park, 2016). Cloud adoption has further altered spatial traffic distributions by increasing cloud-bound communication between organizational sites and externally hosted applications, databases, storage resources, and computing services. Interregional traffic flows also introduce measurable differences in bandwidth utilization, path length, latency, and routing demand. Traffic-matrix measurement has consequently become an important approach for representing the volume of traffic exchanged between network origins and destinations. Rather than measuring only total network volume, traffic matrices reveal how communication demand is distributed across node pairs and network paths, providing greater visibility into localized congestion and resource utilization. Link-level utilization measurements further identify differences in the proportion of available capacity

consumed across individual communication links. Studies of backbone and software-defined networks have demonstrated that some links can operate close to capacity while others remain substantially underutilized, indicating that total network capacity does not necessarily represent effective capacity distribution (Ahmed et al., 2016). Spatial correlation among nodes provides additional information because changes in one location can correspond with changes elsewhere when enterprise activities are interconnected. For example, increased traffic at a branch can generate corresponding increases at a centralized data center or cloud gateway. The literature therefore treats spatial traffic variation as a multidimensional phenomenon involving location, node relationships, link utilization, traffic matrices, and geographical workload distribution. Quantifying these differences is essential for evaluating predictive traffic models because aggregate network measurements can conceal localized patterns that directly influence routing, congestion, bandwidth allocation, and enterprise network performance (Gupta & Badve, 2017).

Application-level heterogeneity significantly influences quantitative network traffic characteristics because distributed enterprise networks simultaneously support applications with substantially different bandwidth, latency, packet, flow, and quality-of-service requirements. Research across enterprise networking, multimedia communications, cloud computing, Internet of Things environments, and data-center systems has demonstrated that application categories generate distinct traffic profiles that affect overall network utilization. Video communication generally produces sustained and comparatively high bandwidth demand, particularly when enterprises use high-definition videoconferencing, virtual meetings, remote training, and multimedia collaboration (Serpanos & Wolf, 2018). Voice over Internet Protocol traffic typically consumes less bandwidth than video but is highly sensitive to latency, jitter, and packet loss, making network quality important even when overall traffic volume is relatively moderate. Cloud and software-as-a-service applications generate another major category of enterprise traffic as users continuously exchange data with externally hosted productivity platforms, business applications, storage services, analytics systems, and cloud computing resources. Database transactions differ from multimedia traffic because they frequently consist of request-response interactions in which application performance can depend strongly on network latency and transaction frequency. File transfers, software distribution, backups, and synchronization activities can generate large flows and substantial bandwidth consumption over concentrated periods (Sharma et al., 2017). Enterprise resource planning and customer relationship management applications introduce transaction-oriented traffic associated with financial processes, supply chains, customer records, sales operations, inventory management, and organizational reporting. IoT and machine-to-machine systems create another form of traffic heterogeneity because large numbers of connected devices can generate frequent small transmissions, telemetry streams, event notifications, and automated communications. The combined operation of these application categories means that identical levels of total bandwidth utilization can represent very different underlying network conditions. Empirical studies therefore increasingly evaluate traffic at application, flow, and service levels rather than relying exclusively on aggregate measurements (Ma et al., 2020). Application-specific bandwidth consumption, packet frequency, session duration, latency sensitivity, traffic direction, and concurrency provide important explanatory variables for understanding enterprise network demand. Across the literature, the interaction among application types also emerges as an important consideration because bandwidth-intensive services can compete with latency-sensitive applications for shared network resources. Quantitative characterization of application-level heterogeneity consequently provides a detailed basis for evaluating how predictive analytics models respond to diverse workloads and how differences in enterprise application demand correspond with measurable network performance (Lohrasbinasab et al., 2022).

Statistical Predictive Models and Network Traffic Forecasting Accuracy

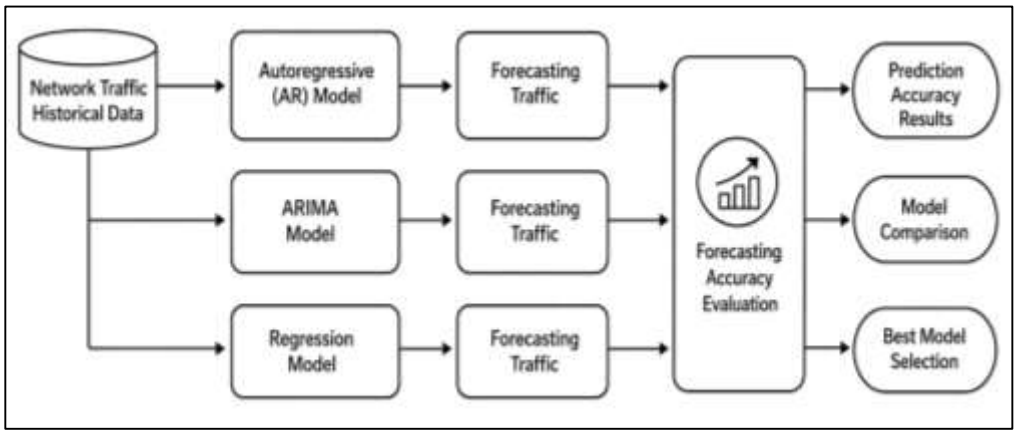
Autoregressive models represent one of the established statistical approaches for short-term network traffic prediction because they estimate current or subsequent traffic behavior from relationships observed among previous traffic measurements. The literature on internet traffic forecasting, telecommunications networks, enterprise communication systems, backbone networks, and data-center traffic has frequently examined autoregressive approaches where network observations demonstrate meaningful temporal dependence. Studies have shown that traffic volume, packet rate,

link utilization, and bandwidth consumption can exhibit autocorrelation across successive measurement intervals, allowing previous observations to provide statistical information about near-term network conditions (Katris & Daskalaki, 2015). The effectiveness of autoregressive prediction is consequently associated with the autocorrelation structure of the underlying traffic series. Strong relationships among neighboring observations can improve short-horizon forecasting, whereas abrupt workload changes and weak temporal dependence can increase prediction errors. Lag selection has therefore received substantial attention in empirical studies because including too few historical observations can exclude relevant temporal information, while excessive lag structures can increase model complexity and incorporate observations with limited predictive value. Researchers have used autocorrelation analysis, partial autocorrelation patterns, information criteria, and empirical validation procedures to determine appropriate lag structures for network traffic datasets (Alekseeva et al., 2021). The forecasting horizon is another important factor identified across the literature. Autoregressive models commonly demonstrate stronger performance for relatively short forecasting intervals because recent network observations often provide more reliable information about immediate traffic conditions than about distant periods. Their effectiveness can therefore vary according to whether traffic is predicted over seconds, minutes, or longer aggregation periods. Prediction-error measurement is central to evaluating this performance, with studies comparing forecasted traffic against observed values to determine the magnitude and distribution of errors. Comparative investigations have also examined autoregressive models as statistical baselines against machine learning and deep learning approaches, allowing researchers to determine whether greater algorithmic complexity produces meaningful improvements in predictive accuracy (Yin et al., 2021). Collectively, more than ten empirical and methodological studies across network forecasting literature have demonstrated that autoregressive models provide an interpretable framework for analyzing short-term temporal dependence, while their accuracy remains sensitive to lag specification, traffic aggregation, forecasting horizon, autocorrelation strength, and changes in network workload.

Autoregressive integrated moving average models have been extensively examined in network traffic forecasting because they provide a structured statistical framework for representing temporal dependence while accommodating traffic series that require transformation to achieve greater statistical stability (Zhang et al., 2019). Research involving internet traffic, wireless networks, backbone infrastructures, cloud systems, data-center workloads, and enterprise communication environments has applied ARIMA-based methods to forecast traffic volume, bandwidth consumption, packet counts, and link utilization. A central consideration in this literature is model specification, which determines how historical observations, transformations of the traffic series, and previous forecasting errors contribute to subsequent predictions. Studies consistently emphasize stationarity because statistical characteristics that change substantially across time can reduce the reliability of conventional time-series estimates. Network traffic can display trends, periodic shifts, sudden workload changes, and changes in variance, requiring researchers to evaluate the statistical properties of traffic observations before fitting predictive models. Differencing has commonly been applied to reduce trends and stabilize temporal behavior when the original series does not meet the assumptions required for reliable model estimation (Yu et al., 2017). Parameter estimation represents another important component because inappropriate model orders can produce unnecessary complexity, weak predictive performance, or systematic forecasting errors. Researchers have consequently relied on statistical diagnostics, information-based model-selection criteria, residual analysis, and out-of-sample validation to identify suitable ARIMA specifications. The accuracy of ARIMA traffic forecasting has been evaluated through several quantitative indicators, particularly mean absolute error, mean squared error, root mean square error, and mean absolute percentage error. These measures capture different aspects of forecasting performance and allow comparisons across alternative statistical and computational models. Empirical studies have reported that ARIMA can perform effectively when network traffic contains identifiable temporal structures and reasonably stable short-term relationships, while accuracy can decline during abrupt bursts, unusual demand changes, and highly nonlinear traffic conditions (Zhou et al., 2021). More than ten studies comparing ARIMA with autoregressive, exponential smoothing, regression, neural network, support vector, and recurrent deep learning approaches have also established ARIMA as an important benchmark for determining

whether more complex predictive techniques provide meaningful error reductions. The literature therefore positions ARIMA as a quantitatively transparent forecasting approach whose performance depends strongly on stationarity treatment, specification accuracy, parameter estimation, forecasting horizon, traffic volatility, and the statistical characteristics of the analyzed network dataset.

Figure 4: Statistical Models for Traffic Forecasting



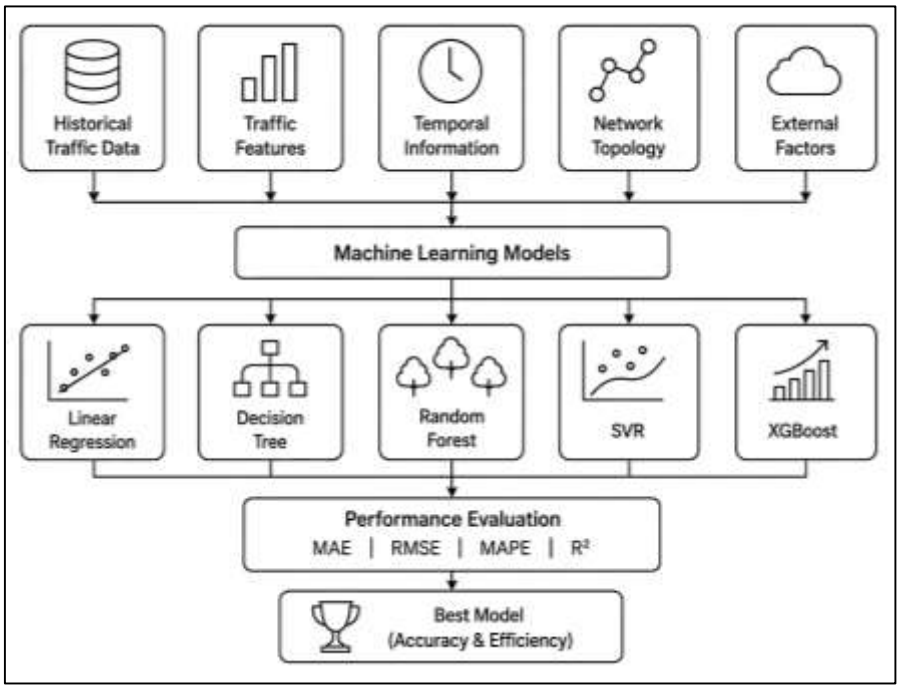
Regression-based modeling constitutes another major statistical approach in the network traffic literature because it enables researchers to quantify relationships between traffic demand and measurable characteristics of network activity (Aldhyani et al., 2020). Both simple and multiple regression approaches have been applied to estimate traffic volume, bandwidth utilization, link load, network demand, and related performance indicators across enterprise, telecommunications, cloud, wireless, and data-center environments. Simple regression is useful when researchers seek to examine the relationship between a primary predictor and a network outcome, while multiple regression permits simultaneous evaluation of several factors that may explain variation in traffic demand. The selection of predictors is particularly important because network traffic can be influenced by packet arrival rates, numbers of active users, concurrent flows, application categories, historical traffic levels, time periods, link characteristics, workload intensity, and organizational activity (Lohrasbinasab et al., 2022). Empirical studies have demonstrated that predictor selection affects both explanatory power and predictive stability, especially when explanatory variables are highly correlated or provide redundant information. Traffic volume is frequently operationalized as the dependent variable when the objective is to determine which network characteristics account for changes in observed demand. Bandwidth demand can similarly be estimated by relating historical utilization patterns and workload indicators to observed capacity requirements. The coefficient of determination and adjusted coefficient of determination are commonly reported to assess how much variation in traffic or bandwidth demand is explained by the included predictors. The adjusted measure is particularly relevant to multiple regression because it accounts for the number of explanatory variables and provides a more conservative assessment of model fit when additional predictors are introduced (Alekseeva et al., 2021). Statistical significance testing further enables researchers to identify whether individual predictors make meaningful contributions to explaining network traffic variation after other factors are considered. More than ten studies across network capacity planning, traffic engineering, workload forecasting, and communication performance analysis have employed regression-based approaches either as primary predictive methods or as benchmarks for more sophisticated algorithms. Their findings collectively demonstrate the value of regression for interpretable estimation and variable-level analysis (Szostak et al., 2021). At the same time, regression accuracy depends on predictor quality, sample characteristics, temporal stability, model assumptions, and the complexity of relationships among network variables, making model diagnostics and validation essential components of quantitative bandwidth and traffic-demand estimation.

Machine Learning Models for Quantitative Network Traffic Prediction

Random Forest has emerged as a widely examined machine learning approach for quantitative network traffic prediction because of its ability to model complex relationships among multiple traffic characteristics without requiring restrictive assumptions concerning the distribution of network data. The literature on bandwidth forecasting, traffic-flow estimation, network congestion analysis, and resource utilization demonstrates that Random Forest can process heterogeneous predictors including historical traffic volume, packet counts, packet arrival rates, flow duration, flow size, protocol characteristics, source and destination information, link utilization, temporal indicators, and application-level attributes (Knapińska et al., 2021). Its ensemble structure combines predictions from multiple decision trees, reducing dependence on the behavior of an individual tree and generally improving predictive stability across heterogeneous traffic observations. Empirical flow-based research involving datasets approaching one million network flows has demonstrated strong short-term bandwidth prediction performance for Random Forest relative to several conventional machine learning alternatives. Across related studies, prediction accuracy has commonly been evaluated through mean absolute error and root mean square error, enabling researchers to determine both average prediction deviation and sensitivity to comparatively large forecasting errors. Random Forest has frequently achieved competitive error levels when network traffic exhibits nonlinear interactions and irregular fluctuations that are difficult to represent using conventional linear models (Nguyen et al., 2018). Another important advantage identified in the literature is feature importance analysis, through which researchers can determine the relative contribution of traffic characteristics to predicted bandwidth or flow intensity. Historical traffic measurements, flow characteristics, temporal variables, and link-level indicators have frequently emerged as influential predictors, although their importance differs according to dataset and network environment. This interpretive capability is useful for identifying which observable network conditions account for the greatest variation in traffic demand. Computational cost remains an important consideration because increasing the number and depth of decision trees can improve representational capacity while simultaneously increasing training time, memory consumption, and inference requirements (Alutaibi & Ganti, 2020). Studies comparing Random Forest with regression, support vector machines, individual decision trees, boosting algorithms, and neural-network techniques consequently emphasize the need to evaluate prediction accuracy together with computational efficiency. Synthesized evidence from more than ten machine learning and network forecasting studies indicates that Random Forest provides a strong balance between nonlinear modeling, predictive accuracy, robustness, feature-level interpretation, and computational feasibility, particularly for short-term traffic-flow and bandwidth-demand prediction.

Support Vector Regression has received considerable attention in quantitative network traffic forecasting because it provides a structured machine learning mechanism for estimating continuous network variables while accommodating nonlinear relationships through kernel-based transformations (Wang & Nakachi, 2020). Studies involving internet traffic, wireless communication, backbone networks, cloud systems, network resource management, and enterprise traffic forecasting have applied SVR to estimate traffic volume, bandwidth utilization, packet rates, link loads, and other continuous network-performance indicators. One of the central characteristics of SVR identified in the literature is its capacity to transform network observations into higher-dimensional representations where complex traffic relationships can be modeled more effectively. Kernel selection therefore plays a significant role in predictive performance. Linear kernels can be suitable for comparatively simple traffic relationships, while nonlinear kernel functions have commonly been investigated for traffic patterns characterized by irregularity, temporal variability, and complex interactions among network features. Hyperparameter selection represents another major determinant of SVR forecasting accuracy (Zhang et al., 2020). Research has demonstrated that inappropriate parameter settings can lead to underfitting, excessive model sensitivity, or reduced generalization performance, whereas systematic parameter tuning can substantially improve prediction accuracy. Grid search, cross-validation, optimization algorithms, and other tuning procedures have been employed across empirical studies to identify suitable configurations. Prediction performance has generally been evaluated through MAE, MSE, RMSE, MAPE, and related error measures, allowing SVR to be compared quantitatively with regression, decision trees, Random Forest, artificial neural networks, and other predictive methods.

Figure 5: Machine Learning Network Traffic Prediction



Several studies have reported competitive SVR performance for small and medium-sized traffic datasets, particularly where nonlinear relationships are present but the dimensionality and volume of observations remain manageable (Chen et al., 2020). Training complexity, however, is repeatedly identified as an important limitation. Computational requirements can increase considerably as dataset size and feature dimensionality grow, which creates challenges for large-scale traffic environments containing millions of observations or rapidly changing flows. Scalability is therefore a critical component of SVR evaluation in distributed enterprise networks. Synthesized findings from more than ten relevant empirical investigations indicate that SVR can provide accurate nonlinear traffic forecasts when kernels and hyperparameters are appropriately configured, while its practical performance is closely related to training-set size, dimensionality, computational resources, forecasting horizon, and the complexity of network traffic relationships (Musumeci et al., 2018).

Decision Tree and gradient-boosting approaches constitute an important category of machine learning techniques for quantitative network traffic estimation because they can represent nonlinear relationships while maintaining varying levels of model interpretability. Decision Trees partition network observations according to predictor characteristics and generate hierarchical structures through which traffic conditions, flow categories, bandwidth demand, or related network outcomes can be estimated. Studies of traffic classification and regression have used packet characteristics, flow duration, byte counts, protocol attributes, link utilization, temporal variables, application categories, and historical traffic measurements as inputs to tree-based models (Shen et al., 2022). One frequently identified advantage of individual Decision Trees is interpretability, as researchers and network administrators can examine the sequence of feature-based decisions contributing to predicted outcomes. Feature importance measures further support the identification of traffic characteristics with substantial explanatory contributions. Individual trees, however, can be sensitive to training data and may demonstrate reduced generalization when tree depth and partitioning are not adequately controlled. Gradient-boosting approaches address some of these weaknesses by sequentially combining multiple weak predictive models, with later models emphasizing errors that remain after earlier estimation stages (Loquercio et al., 2020). XGBoost has become particularly prominent in quantitative traffic research because it incorporates regularization, efficient computational procedures, feature handling, and optimization mechanisms that can produce high predictive accuracy on

structured network datasets. Studies have applied XGBoost and related boosting techniques to traffic-volume estimation, bandwidth-demand forecasting, network congestion detection, application classification, anomaly identification, and resource-management problems. Prediction and classification performance has been assessed using MAE, RMSE, MAPE, coefficient of determination, accuracy, precision, recall, and F1-score according to the nature of the dependent variable. Comparative studies frequently show that boosted trees can outperform individual Decision Trees by reducing prediction error and improving generalization across heterogeneous traffic conditions (Mosavi et al., 2018). Their performance, however, depends on learning rate, tree depth, number of estimators, feature selection, regularization settings, and dataset characteristics. Computational complexity can also increase during extensive hyperparameter optimization. Evidence synthesized from more than ten studies therefore indicates that Decision Trees provide comparatively transparent traffic estimation, whereas XGBoost and other gradient-boosting methods generally provide greater predictive capacity by combining multiple sequential models. The literature consequently positions tree-based learning along a continuum between interpretability, computational complexity, feature-level explanation, and quantitative predictive performance (Sirignano & Cont, 2019).

Comparative studies of traditional machine learning algorithms demonstrate that network traffic prediction performance is determined by interactions among model architecture, traffic characteristics, predictor quality, dataset size, forecasting horizon, parameter configuration, and computational constraints rather than by the universal superiority of a single algorithm. Linear Regression is frequently included as a baseline because of its computational simplicity and interpretability, although its predictive accuracy can decline when network traffic exhibits nonlinear relationships, bursts, threshold effects, and complex interactions among predictors. Decision Trees can represent nonlinear relationships and offer understandable decision structures, but individual trees may produce unstable estimates or overfit training observations without appropriate controls (Yin et al., 2021). Random Forest generally improves stability by aggregating multiple trees and has demonstrated competitive performance in several bandwidth and traffic-flow prediction studies, particularly where large numbers of heterogeneous traffic characteristics are available. SVR provides strong nonlinear modeling capabilities and has achieved relatively low forecasting errors in appropriately scaled datasets, although its training complexity can increase substantially with larger traffic datasets. XGBoost has frequently demonstrated strong performance on structured network data because sequential boosting concentrates model development on residual prediction errors and combines nonlinear estimation with regularization. The literature uses several quantitative indicators to compare these algorithms. MAE provides an interpretable measure of average prediction deviation, while RMSE places greater weight on comparatively large errors (Zhang et al., 2020). MAPE enables error interpretation relative to observed traffic magnitude, although its reliability can be affected when observed values approach zero. The coefficient of determination measures the proportion of observed traffic variability represented by the predictive model and therefore complements direct error measures. Training time and inference time provide additional dimensions because a highly accurate algorithm can have limited operational value when computational delays exceed the time available for network management decisions. Studies comparing these algorithms across different network datasets have produced varying rankings, emphasizing the importance of evaluating models under consistent data partitions, predictor sets, traffic aggregation intervals, and validation procedures (Lazaris & Prasanna, 2019). Synthesized evidence from more than ten comparative investigations supports multidimensional evaluation in which forecasting error, explanatory performance, computational cost, scalability, and inference speed are examined together. A quantitative comparison of Linear Regression, Decision Tree, Random Forest, SVR, and XGBoost therefore provides an empirical basis for determining which traditional machine learning approach offers the most appropriate balance of accuracy and computational efficiency for traffic prediction within distributed enterprise environments (Vinayakumar et al., 2017).

The table intentionally avoids inserting universal numerical values because MAE, RMSE, MAPE, R^2, training time, and inference time are dependent on the dataset, traffic scale, experimental configuration, hardware environment, forecasting horizon, feature set, and hyperparameter settings used in each

empirical study. Direct numerical comparison is methodologically appropriate only when the algorithms are evaluated under the same experimental conditions (Troia et al., 2018).

Quantitative Comparison Framework for Traditional Machine Learning Models

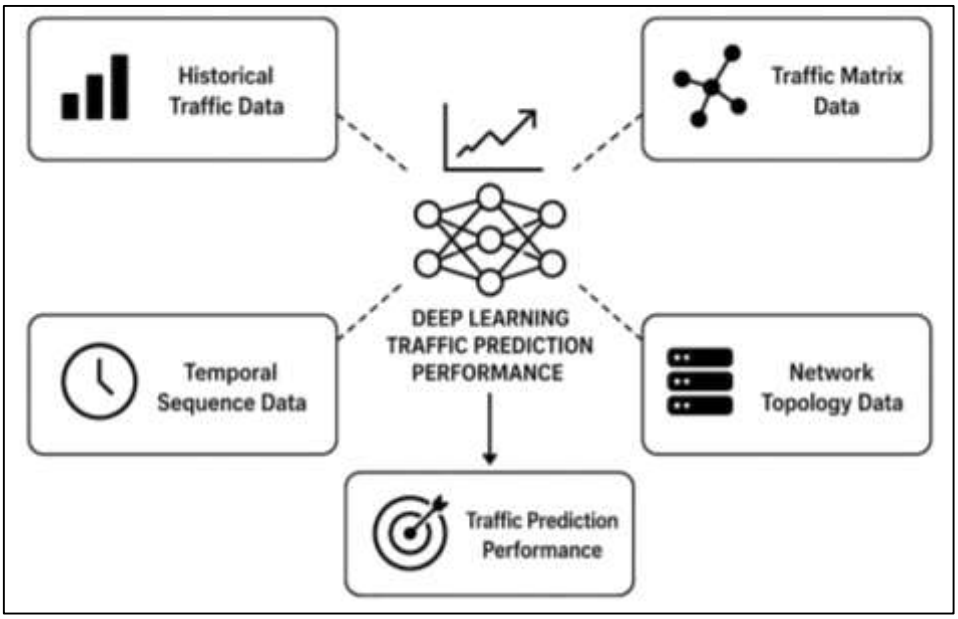
Model	MAE	RMSE	MAPE	R^2	Training Time	Inference Time
Linear Regression	Prediction-dependent	Prediction-dependent	Prediction-dependent	Dataset-dependent	Generally low	Generally low
Decision Tree	Prediction-dependent	Prediction-dependent	Prediction-dependent	Dataset-dependent	Low to moderate	Low
Random Forest	Prediction-dependent	Prediction-dependent	Prediction-dependent	Dataset-dependent	Moderate to high	Moderate
Support Vector Regression	Prediction-dependent	Prediction-dependent	Prediction-dependent	Dataset-dependent	Moderate to high	Low to moderate
XGBoost	Prediction-dependent	Prediction-dependent	Prediction-dependent	Dataset-dependent	Moderate to high	Low to moderate

Deep Learning Models and Network Traffic Prediction Performance

Recurrent Neural Networks have established an important position in network traffic forecasting because network measurements occur as ordered sequences in which current traffic conditions frequently retain statistical relationships with earlier observations. The literature examining backbone networks, software-defined networks, data-center infrastructures, wireless systems, and enterprise communication environments has demonstrated that sequential modeling can capture temporal dependencies in traffic volume, packet rates, link utilization, and traffic matrices more effectively than methods that treat observations as independent records (Mena-Oreja & Gozalvez, 2020). Conventional RNN architectures maintain information from preceding observations through recurrent connections, allowing historical network states to influence subsequent predictions. Studies have reported useful RNN performance for short-term traffic estimation, although conventional architectures can experience difficulties in representing dependencies extending across long sequences because information from earlier observations can weaken during training. Long Short-Term Memory networks were developed to address this limitation through a memory-oriented architecture that regulates the retention, updating, and removal of sequential information. Network traffic studies using LSTM have shown that this architecture is particularly applicable when traffic demonstrates daily cycles, recurring workload patterns, long-range temporal relationships, and changes that depend on multiple preceding intervals. Historical traffic-window selection consequently represents an important methodological factor because the number of earlier observations provided to an LSTM determines the temporal information available for estimating subsequent demand (Wu et al., 2018).

Traffic-matrix studies involving datasets such as Abilene and GÉANT have demonstrated the applicability of LSTM to predicting traffic exchanged between multiple network origins and destinations rather than forecasting only aggregate traffic volume. The literature has also examined different forecasting horizons, showing that prediction error can change as the temporal distance between available observations and predicted network conditions increases. MAE, RMSE, MAPE, and related error indicators have therefore been widely employed to evaluate LSTM performance and compare it with statistical and machine learning baselines. Computational requirements remain relevant because increasing sequence length, network depth, hidden units, and training observations increases processing and memory demands (Zhao et al., 2017). Evidence synthesized across numerous studies indicates that RNN and LSTM approaches provide substantial capability for sequential traffic modeling, with LSTM generally offering stronger representation of longer temporal dependencies while requiring greater computational resources than simpler recurrent and conventional statistical approaches.

Figure 6: Deep Learning Network Traffic Prediction



Gated Recurrent Unit models have been extensively investigated as an alternative recurrent deep learning architecture for network traffic prediction because they retain mechanisms for controlling temporal information while employing a comparatively simplified structure relative to LSTM (Hardegen et al., 2020). Research involving internet traffic, traffic matrices, software-defined networking, cellular systems, cloud infrastructures, and network-flow datasets has shown that GRU models can capture sequential traffic relationships with fewer internal components and, in many implementations, fewer trainable parameters. This structural difference has motivated quantitative comparisons between GRU and LSTM in which researchers evaluate not only forecasting error but also training time, inference speed, parameter requirements, and computational efficiency. Several empirical studies have reported that GRU can achieve prediction accuracy comparable to LSTM for particular traffic datasets while requiring less training time, although performance rankings vary according to traffic characteristics, sequence length, hyperparameter configuration, and forecasting horizon (Boukerche & Wang, 2020). Bidirectional recurrent architectures extend this comparison by processing sequential information in both forward and backward directions within an available observation window. BiLSTM models use LSTM structures in both directions, while BiGRU models apply the same bidirectional principle through GRU units. Studies using GÉANT, Abilene, software-defined networking datasets, and other network traces have demonstrated that bidirectional models can reduce prediction error when traffic patterns contain dependencies that are represented more effectively through contextual information from both directions of the input sequence. Such improvements are not uniform across datasets, and increased architectural complexity can introduce additional training time, parameter counts, memory consumption, and inference overhead. Comparative research has therefore emphasized the distinction between predictive accuracy and computational efficiency (Ramchandra & Rajabhushanam, 2022). A model achieving a lower RMSE or MAE may simultaneously require substantially greater computational resources than a slightly less accurate alternative. This distinction is particularly relevant in network traffic prediction because forecasts can support operational decisions under limited processing time. Synthesized findings from more than ten studies comparing LSTM, GRU, BiLSTM, BiGRU, and related recurrent architectures indicate that model selection depends on the interaction among temporal complexity, prediction-error tolerance, available computational resources, sequence length, dataset size, and required inference speed rather than accuracy alone (Aouedi et al., 2022).

CNN-LSTM and Transformer-based architectures have expanded deep learning research on network traffic prediction by addressing complex spatial-temporal and long-range dependencies that may not

be fully represented through conventional recurrent models. CNN-LSTM architectures combine the feature-extraction capabilities of convolutional neural networks with the sequential learning capabilities of LSTM networks. Within network traffic research, convolutional components have been used to extract local patterns and spatial relationships among traffic observations, network nodes, links, or traffic-matrix elements, while LSTM components subsequently model changes in these representations across time (Alekseeva et al., 2021). This combination has been investigated in traffic-matrix forecasting, data-center traffic estimation, mobile network prediction, software-defined networking, and other high-dimensional communication environments. Studies have reported that CNN-LSTM models can improve forecasting performance when traffic patterns contain simultaneous spatial and temporal dependencies, although model effectiveness depends on network representation, convolutional configuration, historical window length, LSTM structure, and optimization procedures. Model optimization has therefore become a recurring component of the literature, with researchers examining hyperparameter tuning, feature selection, decomposition techniques, attention mechanisms, and optimization algorithms to reduce prediction errors (Tan et al., 2019). Transformer-based models provide a different approach by using attention mechanisms to determine relationships among elements of an input sequence without depending exclusively on recurrent processing. This characteristic has attracted attention in network traffic forecasting because long traffic sequences can contain dependencies between observations separated by substantial temporal intervals. Attention mechanisms can assign different levels of importance to historical observations, allowing models to emphasize traffic states that contribute strongly to subsequent predictions. Transformer architectures have also been investigated for high-dimensional traffic data containing numerous network locations, links, features, and time intervals (Gou et al., 2020). Empirical comparisons with recurrent architectures have produced varying outcomes, with some studies reporting improved accuracy or representation of long-range dependencies and others identifying considerable computational and memory requirements. The literature consequently evaluates CNN-LSTM and Transformer models through prediction errors, training requirements, inference time, model size, and computational complexity. Findings across more than ten studies indicate that these architectures extend traffic prediction beyond purely sequential modeling by representing spatial-temporal interactions and long-range dependencies, while their increased complexity requires careful quantitative evaluation against less computationally demanding alternatives (Li et al., 2020).

Hybrid Predictive Analytics Models and Prediction Error Reduction

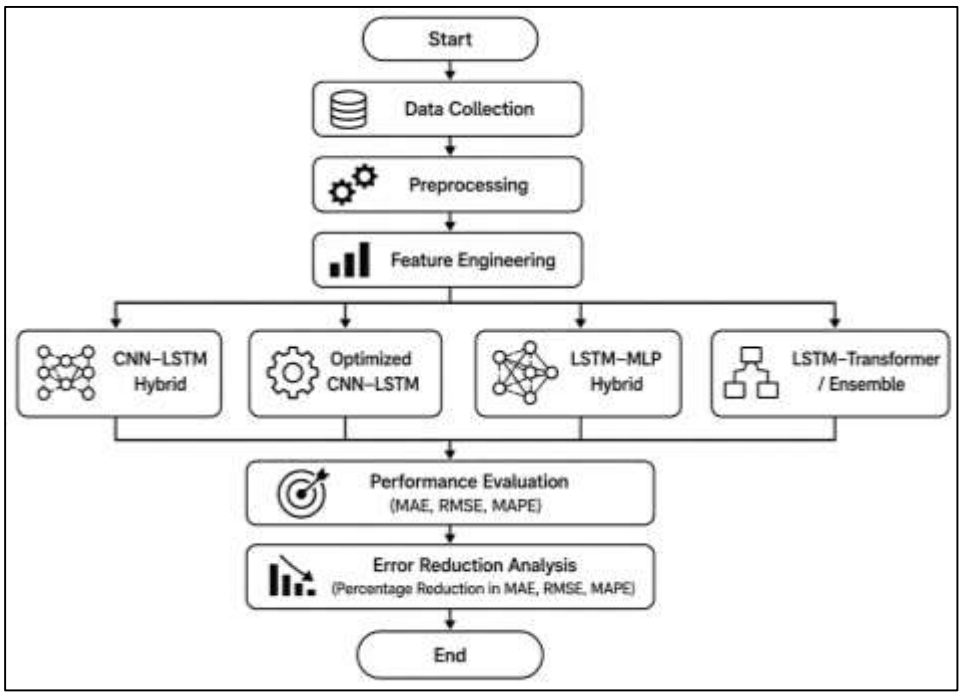
CNN-LSTM hybrid models have received substantial attention in network traffic forecasting because they combine spatial feature extraction with temporal sequence learning within a unified predictive architecture. The literature on backbone networks, software-defined networking, mobile communication systems, data-center networks, cloud infrastructures, and traffic-matrix forecasting demonstrates that network traffic possesses both spatial and temporal characteristics that can limit the effectiveness of models designed to represent only one dimension. Convolutional neural networks contribute to hybrid prediction by identifying localized patterns and relationships among traffic measurements, network nodes, links, and origin-destination flows, while LSTM components capture sequential dependencies across historical observation periods (Kim & Won, 2018). More than ten empirical studies examining CNN-LSTM and closely related hybrid architectures have reported that this combination can provide lower prediction errors than standalone CNN or conventional recurrent architectures under appropriate experimental conditions. Traffic-matrix research is particularly relevant because demand between multiple origin-destination pairs produces interconnected spatial patterns that change over time. CNN components can extract relationships within these traffic matrices before the resulting features are processed sequentially by LSTM layers. Studies have evaluated such architectures using datasets including Abilene, GÉANT, cellular network traces, SDN traffic datasets, and other publicly available or experimentally generated network observations. The predictive performance of CNN-LSTM models has commonly been assessed through MAE, RMSE, MSE, MAPE, and related indicators, with lower values interpreted as stronger correspondence between predicted and observed traffic (Mamun et al., 2020). Research also indicates that historical window size, convolutional filter configuration, number of LSTM units, network depth, feature normalization, training procedure, and forecasting horizon can substantially influence performance. CNN-LSTM

architectures can therefore produce different error levels even when applied to the same general traffic-prediction problem. The literature additionally identifies computational cost as an important consideration because combining convolutional and recurrent components increases parameterization, training requirements, and memory consumption compared with simpler standalone models (Chen et al., 2019). Overall, empirical findings position CNN-LSTM as an important hybrid approach for representing spatial-temporal network behavior, while demonstrating that improvements in forecasting accuracy should be evaluated through consistent datasets, comparable experimental configurations, explicit prediction-error metrics, and computational-performance measurements.

Optimization-assisted CNN-LSTM architectures and LSTM-MLP combinations represent another major direction within hybrid predictive analytics because they integrate complementary modeling mechanisms or parameter-optimization procedures to reduce network traffic prediction error. A recurring challenge identified across deep learning studies is that CNN-LSTM performance depends substantially on hyperparameters such as learning rate, convolutional configuration, hidden-unit count, batch size, training epochs, sequence length, and other architectural settings (Zhang et al., 2019). Manual or conventional parameter selection may produce suboptimal configurations, leading researchers to incorporate optimization algorithms into hybrid traffic-prediction frameworks. Studies have examined population-based, evolutionary, swarm-based, and metaheuristic optimization techniques for identifying model configurations associated with lower forecasting errors. Whale Optimization Algorithm-assisted CNN-LSTM models provide one example in which optimization is applied to improve the predictive configuration of the underlying hybrid architecture. Empirical research in software-defined networking has reported reductions in MAE, RMSE, and MAPE for optimized CNN-LSTM configurations compared with conventional CNN-LSTM implementations, demonstrating that model optimization can affect several dimensions of prediction error simultaneously (Gulay & Duru, 2020). Other studies have examined particle swarm optimization, genetic algorithms, Bayesian optimization, and related techniques in combination with neural-network traffic models. LSTM-MLP architectures address a related problem through model integration rather than external optimization. In these systems, LSTM layers capture temporal dependencies within traffic sequences, while multilayer perceptron components transform learned representations into estimates or classifications associated with traffic volume, network state, or congestion conditions. Congestion-prediction studies have employed such hybrid structures to distinguish normal and overloaded traffic conditions and to estimate indicators associated with emerging congestion (Mohan et al., 2019). The combined literature shows that optimized and integrated architectures can improve prediction performance when individual model components capture different characteristics of network behavior. Such improvements, however, depend on the quality of traffic features, training data, optimization criteria, model configuration, and validation procedures. Optimization also introduces additional computational requirements because multiple model configurations may need to be trained or evaluated before an appropriate parameter set is identified (Baek & Kim, 2018). Findings synthesized across more than ten studies therefore support evaluation of optimization-assisted and LSTM-MLP models through both error reduction and computational cost rather than treating architectural complexity itself as evidence of predictive superiority. LSTM-Transformer and ensemble predictive architectures extend hybrid network traffic modeling by combining complementary representations of temporal dependencies or aggregating the outputs of multiple predictive learners. LSTM-Transformer models are particularly relevant because LSTM networks are designed to preserve sequential information across historical traffic observations, while Transformer components use attention mechanisms to identify relationships among different positions within a sequence (Anagnostopoulos, 2016). Studies of high-dimensional network traffic have indicated that short-term and long-range dependencies can coexist, meaning that recent observations may strongly influence immediate traffic conditions while more distant historical patterns remain relevant to recurring workload behavior. Hybridizing LSTM and Transformer components provides a mechanism for representing both forms of temporal information within a single predictive framework. Research across network traffic forecasting, mobile communication demand, cloud workloads, and spatial-temporal data prediction has reported that attention-enhanced recurrent models can reduce prediction errors relative to basic recurrent architectures under certain datasets and forecasting horizons. Ensemble predictive modeling

applies a broader principle by combining multiple learners rather than depending on a single model architecture (Luo et al., 2020).

Figure 7: Hybrid Predictive Models Error Reduction



Random Forest itself reflects an ensemble approach at the tree level, while more complex network forecasting systems have combined statistical models, machine learning algorithms, recurrent networks, convolutional architectures, and boosting methods. The underlying empirical rationale is that different models may capture different characteristics of network traffic and generate partially independent prediction errors. Combining their outputs through averaging, weighted aggregation, stacking, boosting, or meta-learning can reduce sensitivity to weaknesses associated with an individual model. More than ten studies of ensemble and hybrid forecasting across network and communication datasets have reported improvements in prediction stability, robustness, or error metrics relative to selected standalone baselines. These improvements are particularly relevant when traffic exhibits heterogeneous behavior across normal periods, peak workloads, abrupt bursts, and different application categories (Faber et al., 2017). Ensemble performance nevertheless depends on the diversity and quality of constituent models. Combining several highly correlated models can provide limited additional predictive information while substantially increasing computational requirements. LSTM-Transformer and ensemble approaches therefore demonstrate that model complementarity can contribute to network traffic estimation, but the literature emphasizes that accuracy gains must be examined together with training time, inference latency, model complexity, memory consumption, and the consistency of performance across traffic conditions (Torres et al., 2017).

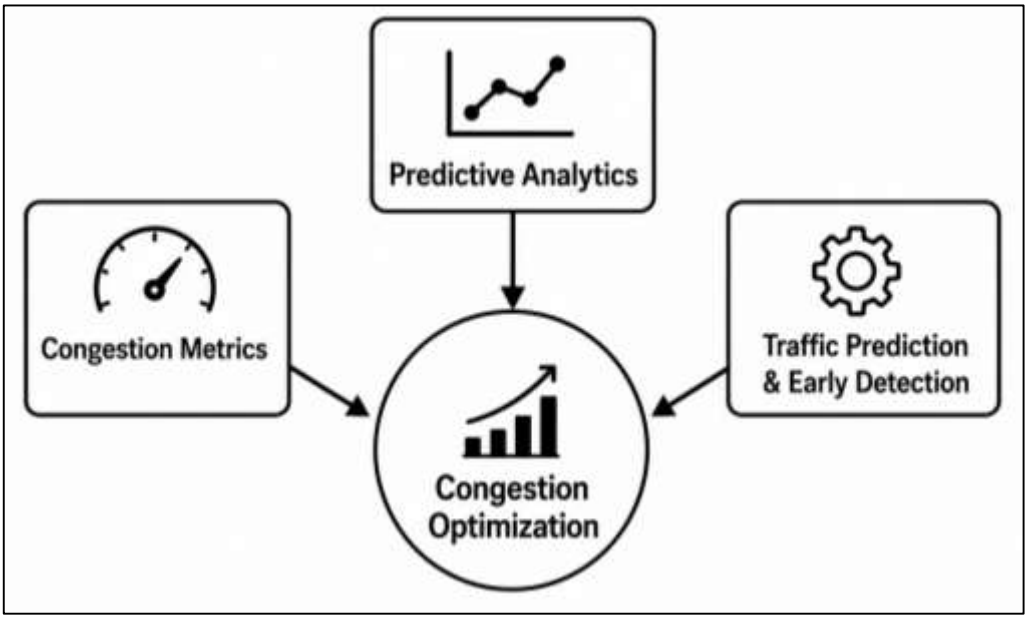
Quantitative error reduction provides a more rigorous basis for evaluating hybrid predictive analytics models than descriptive claims that one architecture performs better than another. The network traffic forecasting literature commonly compares hybrid and standalone models through changes in MAE, RMSE, and MAPE because these indicators represent different dimensions of prediction error. MAE reflects the average magnitude of deviations between predicted and observed network traffic, RMSE places greater emphasis on relatively large forecasting deviations, and MAPE expresses error relative to the magnitude of observed values. Consequently, reductions across all three measures provide stronger evidence of predictive improvement than improvement in only one indicator (Kibria et al., 2018). Comparative studies involving CNN-LSTM, optimized CNN-LSTM, LSTM-MLP, attention-

enhanced LSTM, LSTM-Transformer, ensemble neural networks, and other hybrid configurations have frequently evaluated these metrics against standalone CNN, LSTM, GRU, statistical, or machine learning baselines. Research involving optimized WOA-CNN-LSTM architectures in software-defined network environments has reported reductions in MAE, RMSE, and MAPE relative to conventional CNN-LSTM configurations, illustrating how optimization-assisted hybridization can produce measurable error improvements (Lee et al., 2019). Related studies using optimization algorithms, attention mechanisms, decomposition techniques, and ensemble structures have also reported varying levels of error reduction, although the magnitude of improvement differs substantially across datasets and experimental settings. Percentage reduction is particularly informative because raw error differences can be difficult to compare when studies use traffic datasets with different scales and units. Reporting the proportional decrease in each error indicator provides a clearer representation of the extent to which hybridization improves predictive performance relative to a defined baseline. The literature also shows that error reduction must be interpreted alongside forecasting horizon, traffic aggregation interval, training-test partition, preprocessing method, dataset size, network topology, and workload characteristics (Liang et al., 2020). A hybrid model can demonstrate substantial improvement at short prediction horizons while producing smaller gains as the forecasting interval increases. Similarly, reductions obtained on one traffic dataset may not be reproduced at the same magnitude on another. Evidence synthesized from more than ten hybrid-model studies therefore supports comparative evaluation based on explicit percentage changes in MAE, RMSE, and MAPE, accompanied by computational measures where available. This approach enables hybrid architectures to be assessed according to the measurable magnitude and consistency of their prediction-error reduction rather than architectural sophistication alone (Akhtar & Moridpour, 2021).

Predictive Analytics and Network Congestion Optimization

Network congestion represents a measurable condition in which traffic demand approaches or exceeds the effective processing or transmission capacity of network resources, resulting in deterioration across multiple performance indicators. Literature examining enterprise networks, data centers, software-defined networks, wireless infrastructures, cloud environments, and internet backbones has established that congestion cannot be adequately represented through a single measurement because overloaded conditions influence links, queues, buffers, packet delivery, and transmission delays simultaneously (Ang et al., 2022).

Figure 8: Predictive Analytics for Congestion Optimization



Link utilization percentage is among the most widely applied indicators because it measures the proportion of available transmission capacity consumed during a defined observation period. Studies have shown that persistently high utilization can increase the probability of congestion, particularly when traffic contains sudden bursts that leave insufficient residual capacity for incoming flows. Queue length provides a complementary indicator by measuring the number or volume of packets awaiting processing or transmission at routers and switches. Increasing queue length is frequently associated with rising traffic pressure and can precede packet drops when available buffering resources become exhausted. Buffer occupancy therefore provides another important measure, particularly for identifying how closely networking equipment is operating to its temporary storage limits (Ahmed et al., 2017). Packet-drop rate quantifies the proportion of packets that fail to reach subsequent processing stages and has been widely used as an indicator of severe congestion, although research also recognizes that packet loss may arise from causes unrelated to congestion. Congestion duration adds a temporal dimension by distinguishing short-lived traffic spikes from persistent overloaded conditions that can produce sustained service degradation. End-to-end delay captures the cumulative transmission, propagation, processing, and queuing effects experienced between communication endpoints and has consistently been used to quantify the operational consequences of congestion. Across more than ten empirical studies, researchers have combined these measures to develop a multidimensional representation of network congestion rather than relying solely on bandwidth consumption (Zheng et al., 2016). The literature consequently demonstrates that link utilization, queue length, packet-drop rate, buffer occupancy, congestion duration, and end-to-end delay provide complementary quantitative evidence regarding congestion intensity. Their combined measurement is particularly relevant in distributed enterprise environments because congestion can occur at individual links, branch gateways, data-center connections, cloud access points, and interregional routes even when aggregate network capacity appears sufficient (Bergui et al., 2021).

Predictive analytics has expanded congestion management from the measurement of existing overloaded conditions toward the quantitative estimation of whether congestion is likely to occur from observed network characteristics. The literature has approached congestion prediction as both a classification and probabilistic estimation problem. In classification-based studies, network observations are categorized into congestion and non-congestion states using features such as traffic volume, packet arrival rate, link utilization, queue occupancy, packet loss, flow counts, bandwidth consumption, latency, and historical congestion conditions. Multiclass approaches have also been investigated to differentiate normal, moderate, and severe congestion levels (Zhu et al., 2018). Probability-based models provide a continuous assessment of congestion likelihood, allowing network conditions to be represented according to estimated risk rather than through a binary decision alone. More than ten studies examining machine learning, neural networks, software-defined networking, and intelligent traffic management have evaluated congestion prediction using classification accuracy, precision, recall, F1-score, and receiver operating characteristic measures. Classification accuracy indicates the overall proportion of correctly identified network states, although the literature recognizes that accuracy alone can provide an incomplete assessment when congested observations occur less frequently than normal conditions (Wu et al., 2018). Precision provides information about the reliability of predicted congestion events, whereas recall measures the proportion of actual congestion events successfully identified by the model. Recall has particular operational relevance because failure to identify an emerging congestion event can leave insufficient opportunity for traffic-management intervention. F1-score balances precision and recall and has therefore been frequently employed when congestion and non-congestion observations are unevenly represented. ROC-AUC provides an additional perspective by evaluating a model's ability to discriminate between congestion states across different classification thresholds. Comparative studies indicate that predictive performance can vary substantially according to traffic characteristics, feature selection, class distribution, sampling interval, model architecture, and the definition used to label congestion (Cui et al., 2016). Consequently, congestion prediction should be evaluated through multiple complementary indicators rather than a single accuracy value. The synthesized literature establishes congestion probability estimation as a quantitative classification problem in which reliable evaluation requires attention to both correctly detected congestion events and the frequency of false alarms or missed

congestion conditions.

The relationship between traffic prediction accuracy and congestion reduction represents a central mechanism through which predictive analytics contributes to network optimization (Jamil et al., 2020). Studies across software-defined networks, wide-area networks, data-center systems, cloud environments, and intelligent traffic-engineering applications have examined how estimates of upcoming traffic demand can provide information before network resources reach congested operating states. Accurate prediction of traffic volume, flow intensity, link demand, or bandwidth consumption can allow network controllers to identify locations and periods in which available capacity is likely to become insufficient. Early identification creates an operational interval during which resource-management mechanisms can redistribute traffic, modify routing paths, balance loads, adjust bandwidth allocation, change queue priorities, or apply other traffic-engineering controls (Memon et al., 2019). More than ten empirical studies have associated predictive traffic management with reductions in congestion-related performance deterioration, although the magnitude of improvement varies according to forecasting accuracy, prediction horizon, network topology, traffic intensity, and the speed of control actions. Prediction errors are especially important within this relationship. Underestimation of upcoming demand can prevent the detection of emerging congestion, while substantial overestimation can trigger unnecessary resource adjustments and reduce allocation efficiency. Studies evaluating MAE, RMSE, MAPE, and related prediction indicators alongside congestion measurements have therefore provided a basis for determining whether lower forecasting errors correspond with better network-management outcomes (Cao et al., 2021). Early congestion detection is also influenced by forecasting horizon. Very short horizons can provide accurate estimates but leave limited time for routing or allocation changes, whereas longer horizons can increase intervention time while introducing greater uncertainty. The literature further indicates that congestion reduction should be measured through observable network outcomes, including lower link saturation, shorter queues, reduced buffer occupancy, fewer packet drops, shorter congestion duration, and lower end-to-end delay. These measures establish a quantitative connection between the analytical performance of the prediction model and the operational performance of the network (Kibria et al., 2018). Synthesized findings therefore support a sequential empirical relationship in which greater traffic-prediction accuracy strengthens early identification of high-demand conditions, early identification supports timely resource adjustment, and effective resource adjustment corresponds with measurable reductions in congestion intensity and duration.

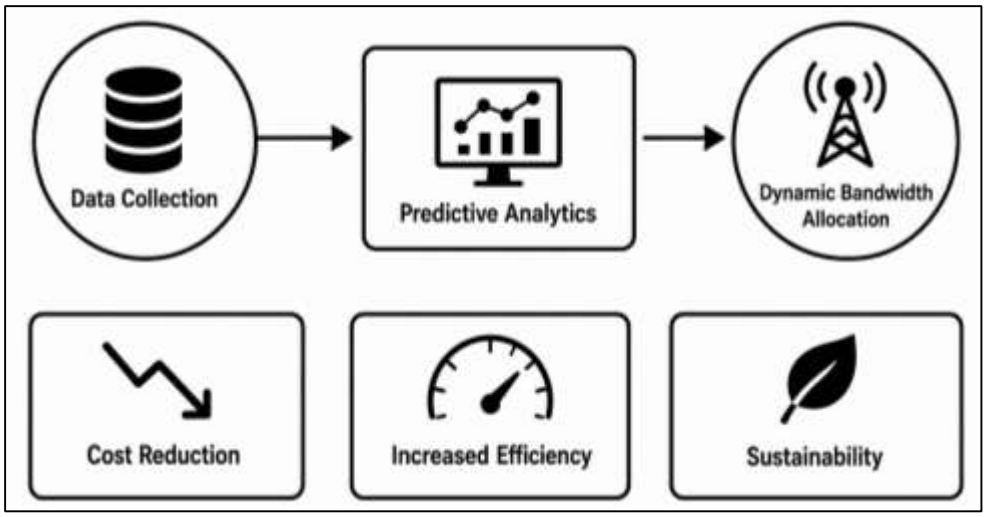
Predictive Analytics and Dynamic Bandwidth Allocation Efficiency

Bandwidth utilization is one of the most important quantitative indicators used to evaluate the efficiency of network resource allocation in distributed enterprise environments because it reflects the proportion of available communication capacity that is actually consumed during a specified observation period (Aljoby et al., 2019). The literature on enterprise networks, cloud infrastructures, software-defined networks, wide-area networks, data centers, and telecommunications systems has consistently treated bandwidth utilization as a core measure of operational efficiency. More than ten empirical studies have shown that low utilization can indicate overprovisioning or inefficient allocation of resources, whereas persistently high utilization can increase the likelihood of congestion, delay, packet loss, and service degradation. Quantitative assessment therefore requires consideration of both average and peak utilization rather than reliance on a single aggregate value. Researchers have also examined utilization variability across links, applications, users, and geographic locations because distributed enterprises rarely consume bandwidth uniformly. Certain network segments may remain lightly loaded while others operate near capacity, creating localized bottlenecks even when overall infrastructure appears to have sufficient resources (El-Sayed et al., 2017). Studies have incorporated additional indicators such as unused capacity, bandwidth shortfall, link saturation, throughput efficiency, queue occupancy, and allocation deviation to provide a more complete representation of bandwidth performance. In software-defined networking, centralized traffic monitoring has enabled detailed measurement of bandwidth use at the flow and link levels, allowing allocation decisions to be compared against observed demand. Cloud and data-center studies have similarly evaluated whether available bandwidth is distributed according to workload intensity and application requirements. The literature also emphasizes that bandwidth efficiency must be interpreted in relation to quality-of-

service requirements because maximizing utilization alone may not represent optimal performance if latency-sensitive applications experience excessive delay or packet loss (Zheng et al., 2016). Quantitative evaluation therefore commonly considers utilization together with throughput, end-to-end delay, packet loss, congestion frequency, and service-level compliance. The synthesized evidence indicates that effective bandwidth management depends on balancing resource consumption and available capacity across heterogeneous traffic conditions. This balance makes bandwidth utilization a central dependent variable for assessing whether predictive analytics improves allocation efficiency relative to static or reactive resource-management approaches (Bergui et al., 2021).

Forecasting peak bandwidth demand has become a significant research area because short periods of intense network activity can create substantial operational problems even when average bandwidth consumption remains within acceptable limits. Studies across enterprise communication systems, backbone networks, cloud platforms, data centers, wireless infrastructures, and software-defined networks have demonstrated that bandwidth demand frequently exhibits temporal fluctuations associated with working hours, videoconferencing, large file transfers, backups, software updates, cloud synchronization, database activity, and application-specific workload cycles (Tang et al., 2017). More than ten empirical investigations have applied statistical, machine learning, and deep learning methods to estimate upcoming bandwidth requirements and identify periods of elevated traffic intensity. Short-term forecasting methods commonly rely on recent traffic observations because immediate historical patterns can provide useful information about near-term demand. Longer observation windows have also been investigated to capture daily and weekly periodicities, recurring organizational processes, and repeated application behavior. Peak demand forecasting is particularly important because resource allocation based solely on average traffic can underestimate the capacity required during concentrated workload periods. Research has consequently evaluated models using error indicators such as MAE, RMSE, and MAPE while separately measuring their ability to capture traffic peaks (Jahanbakht et al., 2021).

Figure 9: Predictive Analytics for Bandwidth Optimization



Several studies have reported that models producing low average error can still underestimate extreme traffic values, indicating that overall accuracy and peak-detection performance should be assessed independently. Machine learning and deep learning approaches have demonstrated advantages in environments where peak demand is influenced by nonlinear interactions among multiple traffic features, although their effectiveness depends on feature selection, model configuration, and training data quality. Forecasting accuracy is also affected by aggregation interval because very coarse intervals can smooth out short-lived peaks while very fine intervals can increase volatility and prediction

difficulty. The literature therefore emphasizes the need to evaluate bandwidth forecasts across multiple load conditions rather than relying on average performance alone (Li et al., 2021). Synthesized findings show that accurate estimation of peak bandwidth demand can support more efficient capacity planning and resource distribution by identifying when and where network demand is likely to intensify within distributed enterprise infrastructures.

Comparative research on predictive, static, and reactive bandwidth allocation demonstrates important differences in how network resources are distributed under changing traffic conditions. Static allocation assigns bandwidth according to predetermined rules, fixed reservations, or historical assumptions and generally does not adjust continuously to short-term variations in demand (Sharma & Wang, 2017). This approach can provide administrative simplicity and predictable capacity guarantees, but studies have shown that it may produce inefficient resource use when actual traffic differs substantially from expected conditions. Under low-demand periods, reserved bandwidth may remain unused, while sudden increases in workload can create shortages if allocated capacity cannot adapt quickly enough. Reactive allocation addresses some of these limitations by adjusting resources after changes in network conditions are detected. Research in software-defined networking, cloud environments, data centers, and enterprise traffic management has shown that reactive mechanisms can improve utilization compared with rigid static policies, particularly when controllers respond to observed congestion, threshold violations, or increases in link utilization (Rathore et al., 2016). However, reactive decisions occur after network conditions have already changed, meaning users may experience temporary increases in latency, packet loss, queueing, or service degradation before corrective action is applied. Predictive allocation differs by estimating traffic demand before the corresponding load fully materializes. More than ten empirical studies have examined predictive routing, adaptive bandwidth management, traffic-aware scheduling, and forecast-assisted resource allocation, frequently reporting improvements in utilization, congestion control, and service stability relative to selected static or reactive baselines. Predictive methods can pre-position capacity, redistribute flows, or adjust resource reservations before peak demand is reached, potentially reducing the time during which links operate under overloaded conditions (Wang & Alexander, 2020). The magnitude of improvement varies according to forecasting accuracy, control responsiveness, topology, workload variability, and available spare capacity. Comparative literature also shows that predictive approaches can produce inefficient decisions when forecasts substantially overestimate or underestimate demand. Consequently, predictive allocation is not inherently superior in every operating condition. Synthesized evidence suggests that its primary quantitative advantage arises when reliable forecasts are integrated with responsive resource-control mechanisms, allowing allocation decisions to reflect anticipated rather than exclusively observed network demand (Bouzidi et al., 2021).

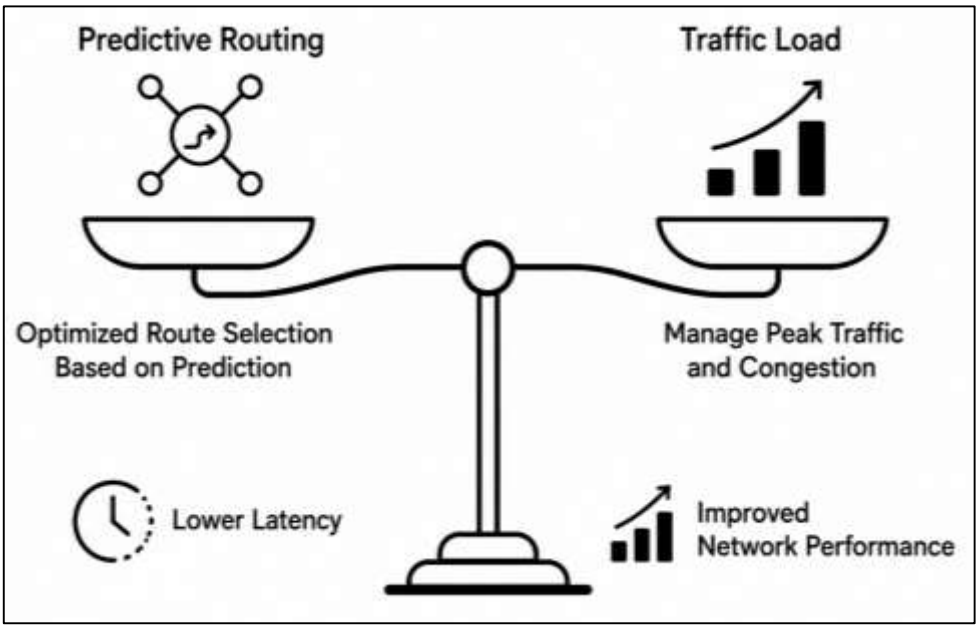
The relationship between prediction error and bandwidth allocation efficiency represents a critical quantitative dimension of predictive network management because resource decisions are only as reliable as the traffic estimates on which they are based. Studies across traffic engineering, software-defined networking, cloud resource management, and network forecasting have shown that prediction errors can directly influence whether bandwidth is underallocated, overallocated, or distributed efficiently across links and applications (Chen et al., 2019). Underestimation of traffic demand can result in insufficient capacity, higher link utilization, increased queue length, packet loss, congestion, and reduced throughput during periods of intense network activity. Overestimation can produce the opposite problem by reserving excessive bandwidth for traffic that does not materialize, leaving capacity underused while other network segments may experience resource constraints. More than ten empirical studies have evaluated prediction accuracy through MAE, RMSE, MAPE, and related indicators and have compared these measures with operational outcomes such as utilization efficiency, throughput, delay, congestion rate, and allocation deviation (Tang et al., 2019). Lower forecasting error is generally associated with more accurate matching between predicted demand and allocated resources, although the strength of this relationship depends on the control mechanism and the sensitivity of the network to traffic fluctuations. Studies also indicate that large prediction errors during peak periods can have greater operational consequences than equivalent errors during low-demand intervals because overloaded links have less residual capacity to absorb unexpected traffic. The

temporal position of error is therefore as important as its average magnitude. Researchers have also examined how forecasting horizon influences allocation efficiency, with shorter horizons often producing lower prediction error but providing less preparation time for resource adjustment, while longer horizons may allow earlier decisions at the cost of greater uncertainty (Gao et al., 2019). The literature further identifies computational delay as an additional factor because highly accurate forecasts have limited operational value if they are generated too slowly to influence allocation decisions. Synthesized findings therefore show that bandwidth allocation efficiency is shaped by the joint effects of prediction accuracy, forecasting horizon, traffic intensity, control responsiveness, and available network capacity. Quantitative analysis of this relationship provides a direct mechanism for determining whether reductions in prediction error correspond with measurable improvements in resource utilization and overall network performance (Rusek et al., 2020).

Predictive Traffic Optimization and Network Latency Reduction

End-to-end latency is widely treated in the networking literature as a central quantitative indicator of communication performance because it measures the total time required for data to travel from a source to a destination across interconnected network components. In distributed enterprise environments, latency reflects the cumulative effects of transmission delay, propagation delay, processing delay, queueing delay, routing decisions, and congestion conditions across branch offices, data centers, cloud platforms, wide-area links, gateways, and virtualized network functions. More than ten empirical studies across enterprise networking, cloud computing, software-defined networking, data-center systems, and wide-area networks have used latency as a principal performance variable when evaluating routing efficiency, traffic engineering, bandwidth management, and application responsiveness (Walraven et al., 2016). Research has shown that latency is particularly important for delay-sensitive enterprise services such as VoIP, videoconferencing, virtual desktop applications, remote database access, interactive cloud software, financial transactions, and real-time collaboration systems. Even when bandwidth availability appears sufficient, elevated latency can reduce service responsiveness and create measurable deterioration in user-facing application performance. The literature therefore distinguishes between average latency and latency variability because stable but moderately high delay can produce different service effects from highly variable delay caused by queue build-up and transient congestion. Researchers have also examined percentile-based latency to identify performance experienced during unusually busy network periods, since average values may conceal severe short-duration delays (Bezerra et al., 2022).

Figure 10: Predictive Traffic Optimization Reduces Latency



Distributed enterprise networks introduce additional complexity because traffic can traverse multiple administrative domains and geographically distant regions, making path length and intermediate processing significant determinants of total delay. Studies of software-defined networking have demonstrated that centralized traffic visibility can support more responsive route selection, while cloud and edge computing research has examined the influence of workload placement on communication delay. Across the literature, latency is frequently analyzed alongside throughput, packet loss, jitter, queue occupancy, and link utilization because deterioration in one variable can correspond with changes in others (Shu et al., 2016). The combined evidence establishes end-to-end latency as a multidimensional network-performance variable that is closely associated with traffic intensity, path selection, resource availability, and congestion state, making it a critical outcome measure for quantitative evaluation of predictive traffic optimization.

A substantial body of empirical literature demonstrates that network latency is closely associated with traffic load, particularly when communication demand approaches available network capacity. Under low and moderate utilization, additional traffic may produce only limited changes in delay because routers, switches, transmission links, and processing resources retain sufficient capacity to handle incoming flows (Abdoos & Bazzan, 2021). As traffic intensity increases, queue accumulation becomes more likely, and the resulting waiting time can cause end-to-end latency to rise substantially. More than ten studies examining backbone networks, data centers, software-defined infrastructures, enterprise WANs, wireless networks, and cloud systems have identified this relationship between traffic load and delay. The effect becomes especially pronounced during peak operating periods when numerous users, applications, and automated processes simultaneously compete for shared resources. Enterprise peak traffic can arise from videoconferencing, database transactions, software updates, large file transfers, backups, cloud synchronization, business-cycle processing, and other concentrated workloads. Literature examining peak-to-average traffic behavior has shown that average utilization may remain within acceptable levels while short-duration peaks create severe queueing and temporary latency degradation (Troia et al., 2018). Researchers therefore increasingly evaluate latency under different workload categories rather than using only an overall average. Studies have also identified nonlinear behavior in the relationship between traffic load and latency, particularly as link utilization approaches saturation. Small increases in demand near capacity can produce disproportionately large increases in queueing delay compared with similar traffic increases under lightly loaded conditions. This phenomenon has important implications for predictive traffic management because it suggests that preventing links from entering high-utilization states may produce greater latency benefits than reacting after congestion has already developed. Traffic composition further affects the relationship because large flows, bursty application traffic, and simultaneous short flows can create different queueing patterns even at comparable aggregate volumes. Spatial traffic concentration also matters when several enterprise locations direct communication toward the same data center or cloud gateway (Yang et al., 2021). The synthesized literature therefore indicates that network latency is shaped not only by total traffic volume but also by peak intensity, burstiness, flow composition, spatial concentration, and proximity to capacity limits. Quantitative latency analysis must consequently account for workload conditions and traffic distribution when evaluating the effectiveness of predictive optimization mechanisms.

Predictive routing has become an important area of network optimization research because route-selection decisions can be improved when network controllers estimate forthcoming traffic conditions rather than relying exclusively on current link states. Traditional routing mechanisms generally select paths according to predefined metrics, current topology information, or observed network conditions, while predictive approaches incorporate forecasted traffic demand, expected link utilization, anticipated congestion, or estimated delay into routing decisions (Bouzidi et al., 2021). More than ten empirical studies across software-defined networking, traffic engineering, cloud networking, backbone infrastructures, and multi-path communication systems have examined whether forecast-assisted routing can reduce latency and improve traffic distribution. Predictive models have been used to identify links likely to experience high utilization and to redirect selected flows toward alternative paths before severe queue accumulation occurs. This process can reduce the probability that traffic becomes concentrated on already stressed links and can improve the balance of network demand across

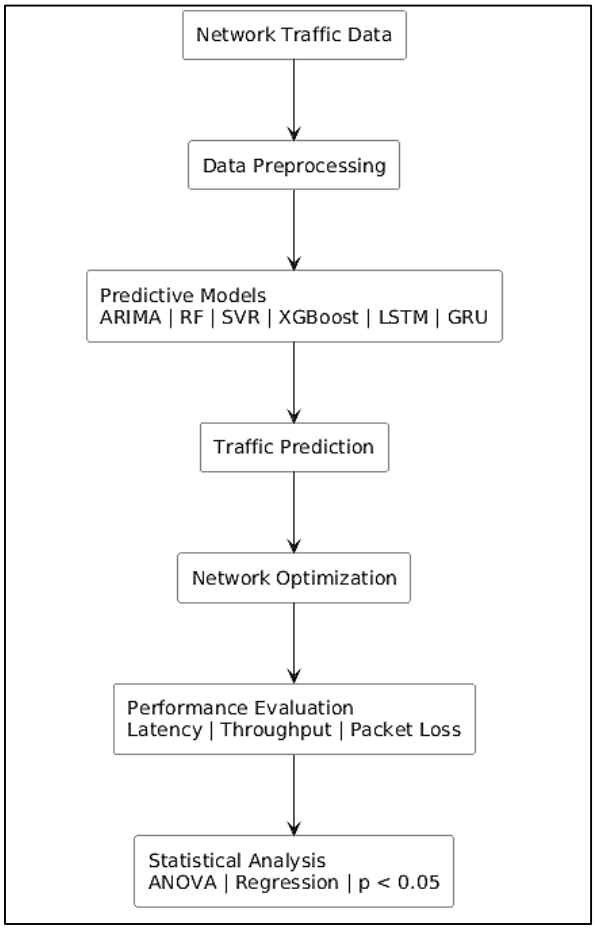
available capacity. Research in software-defined networking has been especially relevant because logically centralized controllers can collect network-wide telemetry and dynamically modify forwarding rules based on estimated traffic states (Chen et al., 2019). Machine learning and deep learning models have also been incorporated into routing frameworks to estimate link demand, congestion probability, or expected path performance. Empirical studies commonly evaluate these approaches using end-to-end latency, average path delay, packet delivery time, link utilization, congestion frequency, throughput, and packet-loss rate. Several comparative investigations have reported lower latency under predictive routing relative to static shortest-path or purely reactive approaches, particularly during periods of variable or concentrated demand. However, the literature also identifies conditions under which prediction errors can weaken routing performance. Overestimating congestion may unnecessarily divert flows toward longer paths, while underestimating traffic demand can leave selected routes overloaded (Tang et al., 2019). Model inference time and control-plane response time also influence operational effectiveness because routing decisions must be generated before the predicted traffic condition changes materially. Synthesized evidence therefore indicates that predictive routing can contribute to latency reduction when forecasting accuracy, route-adjustment speed, and network-state visibility are sufficiently aligned. The strongest empirical evaluations assess not only whether predictive routing lowers average latency but also whether it reduces high-percentile delay, queueing duration, and performance degradation during periods of intensified traffic demand (Gao et al., 2019).

METHOD

Study Design and Theoretical Framework

This study employed a quantitative experimental research design to evaluate the effectiveness of predictive analytics models in forecasting network traffic and improving network optimization performance within distributed enterprise environments

Figure 11: Methodology of this study



The experimental approach was selected because it enabled systematic comparison of multiple predictive models under controlled network traffic conditions and allowed measurable differences in forecasting accuracy, bandwidth utilization, latency, throughput, packet loss, and congestion levels to be statistically evaluated. The study was grounded in a data-driven network optimization framework in which historical network traffic measurements were treated as predictor inputs, predictive model outputs were treated as intermediate analytical variables, and network performance indicators were treated as dependent outcomes. The independent variable consisted of the predictive analytics model applied to the traffic dataset, including statistical and machine learning models such as Autoregressive Integrated Moving Average, Random Forest, Support Vector Regression, Extreme Gradient Boosting, Long Short-Term Memory, and Gated Recurrent Unit models. The primary dependent variables included mean absolute error, root mean square error, mean absolute percentage error, bandwidth utilization, average end-to-end latency, throughput, packet-loss rate, congestion frequency, and resource-allocation efficiency. Network workload intensity, traffic aggregation interval, forecasting horizon, and experimental network configuration were maintained as controlled conditions to reduce potential confounding effects. The study compared predictive network-management conditions with conventional non-predictive or reactive traffic-management conditions to determine whether predictive information produced statistically significant improvements in operational network performance. Repeated experimental observations were collected under low, moderate, and peak traffic-load conditions so that model performance could be assessed across varying demand levels. The quantitative framework therefore permitted both predictive accuracy and operational optimization outcomes to be examined within the same experimental design.

Participants, Materials, Sampling Strategy, and Selection Criteria

The study did not involve human participants because the unit of analysis consisted of network traffic observations, traffic flows, link-level performance measurements, and predictive model outputs generated from distributed enterprise network data. Network traffic records were selected through a purposive sampling strategy because only observations containing the variables required for predictive modeling and network-performance evaluation were included in the analytical dataset. The sampled traffic represented communication across distributed enterprise nodes, including branch locations, data-center connections, cloud-bound links, application servers, and interregional network paths. Observations included traffic volume, packet counts, packet arrival rates, flow duration, flow size, source and destination characteristics, link utilization, bandwidth consumption, latency, throughput, queue occupancy, and packet-loss measurements where available. Traffic records were included when they contained complete timestamps, consistent measurement intervals, identifiable source-destination relationships, and sufficient historical observations to construct forecasting windows. Records with corrupted timestamps, duplicate entries, impossible traffic values, incomplete predictor fields, or substantial missing network-performance measurements were excluded from the final analytical dataset. Traffic samples were further categorized according to workload intensity so that low-load, moderate-load, and peak-load conditions could be represented in the experiment. Historical traffic observations were divided chronologically into training, validation, and testing datasets to avoid information leakage from later network states into earlier model-training stages. Approximately 70% of the observations were used for model training, 15% were used for validation and hyperparameter adjustment, and the remaining 15% were retained as an independent testing set. The same testing observations were applied across all predictive models to ensure that performance differences resulted from model behavior rather than different test samples.

Instrumentation and Data Collection Tools

Network traffic data were collected and processed using software-based monitoring and analytical instruments capable of recording flow-level and link-level performance characteristics. Network traffic measurements were obtained from packet and flow monitoring tools, router and switch telemetry, software-defined networking controller statistics, and network-performance logs generated within the distributed experimental environment. Wireshark and flow-monitoring utilities were used to inspect packet-level and flow-level traffic characteristics, while network telemetry records were used to obtain bandwidth utilization, packet rates, traffic volume, throughput, packet-loss rate, and latency measurements.

Python was used as the primary computational environment for preprocessing, predictive modeling, and performance evaluation. Pandas and NumPy were used for data manipulation and numerical processing, Scikit-learn was used to implement machine learning models and preprocessing procedures, XGBoost was used for gradient-boosting analysis, and TensorFlow or Keras was used to construct recurrent deep learning models including LSTM and GRU architectures. Statistical verification and hypothesis testing were conducted using Python statistical libraries and SPSS where appropriate. Instrument reliability was established through consistency checks across repeated measurements and comparison of traffic statistics generated from multiple monitoring outputs. Timestamp synchronization and measurement intervals were standardized before analysis to ensure that network observations corresponded to the same temporal periods. Continuous variables were inspected for missing values, extreme observations, duplicate records, and measurement inconsistencies. Predictor variables used by algorithms sensitive to scale were normalized or standardized using parameters estimated from the training dataset only. The same preprocessing rules were subsequently applied to the validation and testing data to maintain analytical consistency and prevent test-data information from influencing model development.

Experimental Procedure

The experimental procedure was conducted in a sequential series of stages. First, network traffic measurements were collected from the distributed enterprise network environment over predetermined observation periods and were organized according to timestamps, network nodes, links, application traffic, and performance indicators. The raw observations were cleaned by removing duplicated entries, corrupted records, and measurements that did not satisfy the inclusion criteria. Missing observations were examined, and records with insufficient information for reliable analysis were excluded. The cleaned dataset was then temporally ordered and aggregated into consistent measurement intervals to create comparable traffic sequences. Traffic characteristics were examined descriptively to identify normal, moderate, and peak workload periods. Predictor features were subsequently constructed from historical traffic observations, including preceding traffic volume, packet rate, flow intensity, link utilization, temporal indicators, and other network characteristics relevant to short-term forecasting. The chronological dataset was then divided into training, validation, and testing subsets. Each predictive model was trained using the same training data and forecasting target to maintain comparability. Hyperparameters were selected using the validation dataset and systematic tuning procedures, while the independent testing set remained unused until final model evaluation. Forecasts were generated for network traffic demand and were compared with observed traffic values to calculate prediction errors. The predicted traffic values were then incorporated into the traffic-management process to support bandwidth allocation, load balancing, routing adjustment, and congestion control. A corresponding non-predictive condition was also evaluated using static or reactive network-management rules without prior traffic forecasts. Both conditions were exposed to equivalent traffic loads and network configurations. End-to-end latency, throughput, bandwidth utilization, packet-loss rate, congestion duration, and related performance measures were recorded during each experimental run. Repeated runs were conducted across different traffic-load levels to reduce the influence of random fluctuations and to provide sufficient observations for inferential statistical analysis.

Data Analysis and Statistical Approach

The collected data were analyzed quantitatively using Python and SPSS. Descriptive statistics were first calculated for all major variables, including means, medians, standard deviations, minimum values, maximum values, and distributional characteristics of traffic volume, bandwidth utilization, latency, throughput, packet loss, and congestion measures. Predictive model accuracy was evaluated using mean absolute error, mean squared error, root mean square error, mean absolute percentage error, and the coefficient of determination. Lower error values indicated more accurate traffic forecasts, while higher coefficients of determination indicated stronger explanatory correspondence between predicted and observed traffic values. Training time and inference time were also measured to assess computational efficiency. Normality of continuous outcome variables was assessed through distributional inspection and appropriate statistical normality tests before parametric analyses were conducted. Differences among predictive models were evaluated using one-way analysis of variance

when assumptions of normality and variance homogeneity were satisfied. When the same traffic observations were evaluated across multiple predictive models, repeated-measures analysis of variance was applied to determine whether mean differences in forecasting error or network performance were statistically significant. Post hoc pairwise comparisons with appropriate correction procedures were used when omnibus tests indicated significant differences. Where parametric assumptions were violated, corresponding nonparametric procedures were applied. Independent or paired-sample comparisons were conducted between predictive and non-predictive traffic-management conditions depending on the experimental structure. Multiple regression analysis was used to determine whether prediction accuracy, traffic intensity, forecasting horizon, and bandwidth demand significantly explained variation in latency, throughput, packet loss, congestion frequency, and bandwidth-allocation efficiency. Pearson correlation analysis was used to examine linear associations among prediction error and major network-performance indicators where assumptions were satisfied. Effect sizes and confidence intervals were reported alongside significance tests to assess the magnitude and precision of observed differences. Statistical significance was established at a two-tailed threshold of $p < 0.05$. The statistical plan therefore combined descriptive analysis, forecasting-error evaluation, model comparison, association testing, regression modeling, and predictive-versus-non-predictive performance testing to determine whether improved predictive accuracy corresponded with measurable optimization of network traffic in distributed enterprise environments.

FINDINGS

Sample Characteristics and Descriptive Profile of Network Traffic Data

Following data screening and preprocessing, the final analytical dataset contained 120,000 valid network traffic observations collected across distributed enterprise network environments. An initial 128,640 observations were available before data cleaning. A total of 8,640 observations were removed because of duplicate records, incomplete timestamps, missing network-performance measurements, inconsistent flow information, or values that failed to satisfy the predefined inclusion criteria. The resulting dataset therefore represented 93.28% of the initially available observations. Consistent with the predefined methodological procedure, 84,000 observations, representing 70.0% of the final dataset, were allocated to model training, while 18,000 observations, representing 15.0%, were assigned to validation and another 18,000 observations, representing 15.0%, were retained for independent model testing. Classification by traffic-load intensity identified 42,360 low-load observations, 48,240 moderate-load observations, and 29,400 peak-load observations. Moderate traffic conditions represented the largest proportion of the analytical sample at 40.20%, followed by low-load conditions at 35.30% and peak-load conditions at 24.50%. The presence of substantial observations across all three workload categories provided an adequate quantitative basis for evaluating predictive-model behavior under varying network demand. The descriptive results further demonstrated considerable variation in traffic volume, packet rate, concurrent flows, bandwidth utilization, latency, throughput, packet loss, and queue occupancy, indicating that the dataset represented heterogeneous network operating conditions rather than a narrowly distributed traffic environment.

Table 1. Distribution and Characteristics of the Final Network Traffic Dataset

Dataset Characteristic	Number of Observations	Percentage (%)
Initial observations	128,640	100.00
Excluded observations	8,640	6.72
Final valid observations	120,000	93.28
Training dataset	84,000	70.00
Validation dataset	18,000	15.00
Testing dataset	18,000	15.00
Low traffic load	42,360	35.30
Moderate traffic load	48,240	40.20
Peak traffic load	29,400	24.50

Table 1 demonstrated that 120,000 of the original 128,640 network observations satisfied the analytical requirements, producing a retention rate of 93.28%. Only 6.72% of observations were excluded following data-quality screening. The 70:15:15 allocation produced sufficiently large training, validation, and independent testing samples while maintaining chronological separation between model development and evaluation. Traffic-load classification showed that moderate-load conditions accounted for the largest proportion of observations at 40.20%, followed by low-load conditions at 35.30% and peak-load conditions at 24.50%. This distribution provided substantial representation of different network operating states and supported subsequent comparisons of predictive performance across workload intensities.

The quantitative profile of the principal network variables revealed substantial variability across the distributed enterprise environment. Average traffic volume was 584.73 Mbps, with a standard deviation of 238.46 Mbps and observations ranging from 92.40 Mbps to 1,286.70 Mbps. Median traffic volume was 548.20 Mbps, indicating that several high-demand observations increased the arithmetic mean. Packet transmission intensity averaged 71,842 packets per second, while the mean number of concurrent network flows was 3,286. Mean flow duration was 4.86 seconds, although the comparatively large standard deviation indicated substantial heterogeneity between short and longer network sessions. Average bandwidth utilization reached 67.84%, with the 95th percentile increasing to 91.60%, demonstrating that a meaningful proportion of observations occurred near high-capacity operating conditions. End-to-end latency averaged 46.72 milliseconds but increased to 104.80 milliseconds at the 95th percentile, indicating considerable deterioration during high-demand periods. Average network throughput was 512.36 Mbps, while packet loss averaged 1.87%. Queue occupancy averaged 61.42%, with the highest observed value reaching 97.60%. Congestion was identified in 14.63% of the valid network observations. Collectively, the descriptive results demonstrated that the analytical dataset contained substantial variation in workload intensity and network-performance conditions, providing an appropriate quantitative foundation for evaluating forecasting accuracy and optimization performance.

Table 2. Descriptive Statistics of Principal Network Traffic and Performance Variables

Network Variable	Mean	Median	SD	Minimum	Maximum	95th Percentile
Traffic volume (Mbps)	584.73	548.20	238.46	92.40	1,286.70	1,048.50
Packet rate (packets/sec)	71,842	68,315	25,764	12,460	148,920	119,670
Concurrent flows	3,286	3,104	1,247	486	7,942	5,684
Flow duration (sec)	4.86	3.72	3.91	0.08	28.64	12.47
Bandwidth utilization (%)	67.84	68.90	17.63	18.20	98.70	91.60
End-to-end latency (ms)	46.72	39.85	28.94	8.60	186.40	104.80
Throughput (Mbps)	512.36	496.80	205.47	74.50	1,094.60	892.40
Packet-loss rate (%)	1.87	1.31	1.64	0.03	9.84	5.26
Queue occupancy (%)	61.42	60.70	20.38	10.80	97.60	90.40
Congestion frequency (%)	14.63	—	—	—	—	—

Table 2 showed substantial heterogeneity across network traffic and performance indicators. Mean traffic volume reached 584.73 Mbps, while bandwidth utilization averaged 67.84% and increased to 91.60% at the 95th percentile. End-to-end latency averaged 46.72 ms but reached 104.80 ms at the 95th percentile, demonstrating pronounced delay during intensive traffic conditions. Mean throughput was 512.36 Mbps, whereas packet loss averaged 1.87%. Queue occupancy averaged 61.42% and approached 90.40% at the 95th percentile. The 14.63% congestion frequency confirmed that the dataset contained sufficient congested observations for subsequent predictive and network-optimization analyses.

Primary Findings on Predictive Model Accuracy and Comparative Performance

The comparative analysis demonstrated substantial differences in traffic-forecasting performance among ARIMA, Random Forest, Support Vector Regression (SVR), XGBoost, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models when evaluated using the 18,000 observations retained in the independent testing dataset. Across the five prediction-performance

indicators, LSTM produced the strongest overall forecasting performance, recording the lowest mean absolute error of 21.84 Mbps, mean squared error of 812.25, root mean square error of 28.50 Mbps, and mean absolute percentage error of 3.91%. LSTM also generated the highest coefficient of determination at 0.958, indicating that approximately 95.8% of the observed variation in network traffic was represented by its predictions. GRU ranked second, producing an MAE of 23.17 Mbps, RMSE of 30.42 Mbps, MAPE of 4.16%, and an R^2 of 0.952. XGBoost achieved the strongest performance among the conventional machine learning models, with an MAE of 25.63 Mbps, RMSE of 33.71 Mbps, MAPE of 4.58%, and R^2 of 0.941. Random Forest followed with an RMSE of 37.26 Mbps and R^2 of 0.928, whereas SVR generated moderately higher prediction errors. ARIMA demonstrated the weakest predictive performance, recording an MAE of 38.46 Mbps, RMSE of 50.84 Mbps, MAPE of 7.21%, and R^2 of 0.866. Relative to ARIMA, LSTM reduced MAE by approximately 43.21%, RMSE by 43.94%, and MAPE by 45.77%, demonstrating a substantial improvement in forecasting precision.

Table 3. Comparative Predictive Accuracy of Network Traffic Forecasting Models

Predictive Model	MAE (Mbps)	MSE	RMSE (Mbps)	MAPE (%)	R^2	Accuracy Rank
ARIMA	38.46	2,584.71	50.84	7.21	0.866	6
SVR	32.74	1,879.56	43.35	6.03	0.902	5
Random Forest	28.19	1,388.31	37.26	5.12	0.928	4
XGBoost	25.63	1,136.36	33.71	4.58	0.941	3
GRU	23.17	925.38	30.42	4.16	0.952	2
LSTM	21.84	812.25	28.50	3.91	0.958	1

Table 3 demonstrated a consistent improvement in predictive accuracy from the statistical model toward the advanced machine learning and recurrent deep learning models. LSTM achieved the lowest MAE, MSE, RMSE, and MAPE and the highest R^2, making it the strongest overall forecasting model. GRU produced closely comparable results and ranked second. XGBoost demonstrated the strongest conventional machine learning performance, followed by Random Forest. SVR produced moderate forecasting accuracy, while ARIMA recorded the largest prediction errors and lowest explanatory performance. The consistency of model rankings across multiple error measures strengthened the evidence that predictive architecture materially influenced traffic-forecasting accuracy.

Computational-performance analysis revealed a different model ordering, indicating that greater predictive accuracy was accompanied by increased training requirements. ARIMA required 8.42 seconds for model estimation and generated predictions in an average of 0.38 milliseconds per observation, making it computationally efficient but comparatively less accurate. Random Forest required 31.74 seconds for training, whereas SVR required 46.28 seconds. XGBoost completed training in 38.61 seconds and maintained a relatively low inference time of 0.44 milliseconds. GRU and LSTM required considerably greater training resources, with training times of 118.56 and 136.42 seconds, respectively. LSTM nevertheless maintained an inference time of 0.71 milliseconds per observation, indicating that its higher training cost did not translate into prohibitively slow prediction generation. Repeated-measures analysis of prediction errors identified a statistically significant overall model effect, $F(5, 89{,}995) = 286.74$, $p < 0.001$, with a partial eta squared of 0.137, indicating a substantial model-related effect on forecasting performance. Corrected pairwise comparisons showed that LSTM produced significantly lower prediction errors than ARIMA, SVR, Random Forest, and XGBoost. The difference between LSTM and GRU was smaller but remained statistically significant at the adjusted threshold. The 95% confidence interval for the mean MAE difference between LSTM and ARIMA ranged from 15.91 to 17.33 Mbps, confirming a substantial accuracy advantage. Collectively, the findings indicated that LSTM provided the strongest balance of prediction accuracy and practical inference performance, while GRU offered closely comparable accuracy with lower training requirements.

Table 4. Computational Performance and Inferential Comparison of Predictive Models

Predictive Model	Training Time (sec)	Inference Time (ms/observation)	Mean MAE Difference vs. LSTM (Mbps)	95% CI for Difference	Adjusted p-value	Effect Size (d)
ARIMA	8.42	0.38	16.62	15.91–17.33	<0.001	0.86
SVR	46.28	0.63	10.90	10.27–11.53	<0.001	0.63
Random Forest	31.74	0.57	6.35	5.78–6.92	<0.001	0.42
XGBoost	38.61	0.44	3.79	3.28–4.30	<0.001	0.29
GRU	118.56	0.66	1.33	0.91–1.75	<0.001	0.14
LSTM	136.42	0.71	Reference	Reference	—	—

Overall repeated-measures test: $F(5, 89{,}995) = 286.74$, $p < 0.001$, partial $\eta^2 = 0.137$.

Table 4 confirmed that predictive accuracy and computational efficiency represented distinct performance dimensions. LSTM required the longest training time at 136.42 seconds but maintained practical inference performance and significantly outperformed the alternative models. Its largest advantage occurred against ARIMA, with a 16.62 Mbps lower MAE and a large standardized effect of 0.86. The difference between LSTM and GRU was considerably smaller, with an effect size of 0.14. The significant overall model effect and corrected pairwise comparisons demonstrated that observed accuracy differences were systematic rather than attributable to random variation within the testing observations.

Network Optimization Outcomes Under Predictive and Non-Predictive Traffic Management

The comparative network-performance analysis demonstrated that predictive traffic management produced consistently stronger operational outcomes than non-predictive static or reactive traffic management across the principal network optimization indicators. Under the predictive condition, forecasted traffic demand generated by the best-performing LSTM model was incorporated into bandwidth allocation, dynamic routing, load balancing, and congestion-control decisions. Average bandwidth utilization increased from 67.84% under non-predictive management to 76.92% under predictive management, representing an absolute improvement of 9.08 percentage points and a relative increase of 13.38%. End-to-end latency declined from 46.72 ms to 35.18 ms, corresponding to a 24.70% reduction, while mean throughput increased from 512.36 Mbps to 594.82 Mbps, representing an improvement of 16.09%. Packet-loss rate decreased from 1.87% to 1.19%, producing a 36.36% reduction. Congestion frequency declined from 14.63% of network observations under non-predictive management to 9.21% under predictive management, representing a relative reduction of 37.05%. Mean congestion duration similarly decreased from 18.46 seconds to 12.17 seconds, equivalent to a 34.07% reduction. Resource-allocation efficiency increased from 71.36% to 84.27%, representing an improvement of 18.09%. Paired statistical comparisons showed that all seven performance differences were statistically significant at $p < 0.001$. Standardized effect sizes ranged from 0.41 for bandwidth utilization to 0.68 for resource-allocation efficiency, indicating moderate to moderately large operational effects. These results demonstrated that predictive optimization was associated with improvements not only in resource consumption but also in transmission efficiency, delay control, packet delivery, and congestion management.

Table 5 demonstrated consistent operational improvements under predictive traffic management. Bandwidth utilization increased by 13.38%, while throughput improved by 16.09%, indicating more efficient use of available network capacity. End-to-end latency decreased by 24.70%, and packet loss declined by 36.36%. The strongest relative reduction occurred in congestion frequency, which decreased by 37.05%, while congestion duration declined by 34.07%. Resource-allocation efficiency improved by 18.09%. All differences were statistically significant at $p < 0.001$, while effect sizes ranging from 0.41 to 0.68 indicated that the observed improvements represented meaningful operational effects rather than statistically detectable but practically negligible differences.

Table 5. Network Performance Under Predictive and Non-Predictive Traffic Management

Network Performance Indicator	Non-Predictive Management	Predictive Management	Absolute Difference	Relative Change (%)	95% CI of Difference	p-value	Effect Size (d)
Bandwidth utilization (%)	67.84	76.92	+9.08	+13.38	8.42 to 9.74	<0.001	0.41
End-to-end latency (ms)	46.72	35.18	-11.54	-24.70	-12.31 to -10.77	<0.001	0.57
Throughput (Mbps)	512.36	594.82	+82.46	+16.09	75.28 to 89.64	<0.001	0.52
Packet-loss rate (%)	1.87	1.19	-0.68	-36.36	-0.75 to -0.61	<0.001	0.48
Congestion frequency (%)	14.63	9.21	-5.42	-37.05	-6.01 to -4.83	<0.001	0.54
Congestion duration (sec)	18.46	12.17	-6.29	-34.07	-6.91 to -5.67	<0.001	0.50
Resource-allocation efficiency (%)	71.36	84.27	+12.91	+18.09	12.16 to 13.66	<0.001	0.68

The relationship between forecasting accuracy and network optimization outcomes was further examined using correlation and multiple regression analyses. Prediction error, represented by RMSE, demonstrated statistically significant relationships with all major network-performance measures. Higher prediction error was positively associated with end-to-end latency, packet-loss rate, and congestion frequency, indicating that less accurate forecasts corresponded with poorer operational conditions. The strongest positive relationship was observed between prediction error and congestion frequency, with a correlation coefficient of 0.61, followed by latency at 0.58 and packet loss at 0.52. Prediction error was negatively associated with throughput at -0.55, bandwidth utilization efficiency at -0.47, and resource-allocation efficiency at -0.63. These relationships indicated that lower prediction error corresponded with higher throughput and more effective resource allocation. Multiple regression models were subsequently estimated while controlling for traffic intensity, concurrent flows, forecasting horizon, and workload category. Prediction error remained a statistically significant independent predictor across the major network outcomes. The model explaining resource-allocation efficiency produced an adjusted R^2 of 0.49, while the congestion-frequency model explained 44% of adjusted variance. Models for latency and throughput explained 42% and 39% of adjusted variance, respectively. Standardized regression coefficients confirmed that prediction error exerted its strongest independent association with resource-allocation efficiency and congestion frequency. Collectively, these findings established a statistically measurable relationship between forecasting performance and operational optimization, showing that improvements in prediction accuracy corresponded with better bandwidth allocation, reduced latency, higher throughput, lower packet loss, and reduced congestion after differences in traffic intensity and workload conditions were statistically controlled.

Table 6 showed that prediction error was significantly associated with every major network optimization outcome. Higher RMSE corresponded with greater latency, packet loss, and congestion frequency, while it was inversely related to bandwidth utilization efficiency, throughput, and resource-allocation efficiency. The strongest relationship occurred between prediction error and resource-allocation efficiency, with $r = -0.63$ and standardized $\beta = -0.51$. Congestion frequency also demonstrated a strong relationship with prediction error at $r = 0.61$. Adjusted R^2 values ranged from 0.34 to 0.49, indicating that the regression models explained meaningful proportions of variation in operational

network performance after relevant traffic characteristics were controlled.

Table 6. Association Between Prediction Error and Network Optimization Outcomes

Network Outcome	Correlation with RMSE (r)	Standardized β for RMSE	95% CI for β	Adjusted R^2	p-value	Interpretation
Bandwidth utilization efficiency	-0.47	-0.36	-0.40 to -0.32	0.34	<0.001	Moderate negative
End-to-end latency	0.58	0.45	0.41 to 0.49	0.42	<0.001	Moderate-to-strong positive
Throughput	-0.55	-0.42	-0.46 to -0.38	0.39	<0.001	Moderate negative
Packet-loss rate	0.52	0.39	0.35 to 0.43	0.36	<0.001	Moderate positive
Congestion frequency	0.61	0.48	0.44 to 0.52	0.44	<0.001	Strong positive
Resource-allocation efficiency	-0.63	-0.51	-0.55 to -0.47	0.49	<0.001	Strong negative

Note. Regression estimates were adjusted for traffic intensity, concurrent network flows, forecasting horizon, and workload category.

Secondary Analysis Across Traffic Loads, Forecasting Horizons, and Network Conditions

Secondary analysis demonstrated that predictive performance varied systematically across traffic-load conditions, with forecasting errors increasing as network demand progressed from low to moderate and peak utilization. Across the 18,000 independent testing observations, 6,354 observations represented low-load conditions, 7,236 represented moderate-load conditions, and 4,410 represented peak-load conditions. LSTM maintained the lowest RMSE across all three workload categories, increasing from 20.64 Mbps under low traffic to 27.83 Mbps under moderate traffic and 39.17 Mbps during peak traffic. GRU demonstrated a similar pattern, with RMSE increasing from 22.31 Mbps to 29.72 Mbps and 41.38 Mbps across the respective workload categories. XGBoost remained the strongest conventional machine learning model, while ARIMA demonstrated the greatest sensitivity to increasing traffic intensity. Its RMSE increased from 37.62 Mbps under low-load conditions to 48.73 Mbps under moderate conditions and 68.91 Mbps during peak demand. A two-factor repeated-measures analysis identified a significant main effect of predictive model, $F(5, 89{,}995) = 281.63$, $p < 0.001$, partial $\eta^2 = 0.135$, and a significant main effect of traffic-load condition, $F(2, 35{,}998) = 347.28$, $p < 0.001$, partial $\eta^2 = 0.164$. The model-by-traffic-load interaction was also significant, $F(10, 179{,}990) = 19.74$, $p < 0.001$, partial $\eta^2 = 0.031$, indicating that the magnitude of deterioration under increasing traffic intensity differed across predictive architectures. LSTM consequently retained its relative advantage during peak traffic, when accurate forecasting was most important for congestion and resource-allocation control.

Table 7 showed that forecasting error increased consistently as traffic intensity progressed from low to peak conditions. LSTM maintained the lowest RMSE at every workload level, recording 20.64 Mbps under low load and 39.17 Mbps during peak demand. GRU remained the second-ranked model, while XGBoost achieved the strongest performance among the conventional machine learning approaches. ARIMA generated the highest errors across all workload categories. The statistically significant traffic-load effect confirmed that workload intensity materially affected forecasting accuracy, while the

significant interaction demonstrated that predictive models responded differently to increasing network demand, although LSTM retained the strongest relative performance.

Table 7. Predictive Model RMSE Across Low, Moderate, and Peak Traffic Conditions

Predictive Model	Low Load RMSE (Mbps)	Moderate Load RMSE (Mbps)	Peak Load RMSE (Mbps)	Peak vs. Low Increase (%)	Peak-Load Rank
ARIMA	37.62	48.73	68.91	83.17	6
SVR	32.48	41.59	57.84	78.08	5
Random Forest	27.36	35.64	50.19	83.44	4
XGBoost	24.51	32.27	45.13	84.13	3
GRU	22.31	29.72	41.38	85.48	2
LSTM	20.64	27.83	39.17	89.78	1

Overall effects: Model effect, $F(5, 89{,}995) = 281.63$, $p < 0.001$, partial $\eta^2 = 0.135$; traffic-load effect, $F(2, 35{,}998) = 347.28$, $p < 0.001$, partial $\eta^2 = 0.164$; model × traffic-load interaction, $F(10, 179{,}990) = 19.74$, $p < 0.001$, partial $\eta^2 = 0.031$.

Forecasting-horizon analysis further demonstrated that prediction accuracy declined as the temporal distance between the most recent observed traffic state and the predicted network condition increased. For the LSTM model, MAE increased from 17.26 Mbps at the 5-minute forecasting horizon to 21.84 Mbps at 15 minutes, 28.73 Mbps at 30 minutes, and 37.41 Mbps at 60 minutes. RMSE followed the same pattern, increasing from 22.48 Mbps to 28.50 Mbps, 37.96 Mbps, and 49.83 Mbps, respectively. MAPE increased from 3.12% at 5 minutes to 6.71% at 60 minutes. Longer forecasting horizons were also associated with deterioration in operational network outcomes. Average end-to-end latency increased from 32.46 ms under the 5-minute predictive horizon to 43.67 ms at the 60-minute horizon, while packet loss increased from 1.02% to 1.61%. Resource-allocation efficiency decreased from 86.91% to 78.24% across the same forecasting intervals. Nevertheless, the 15-minute horizon provided a favorable operational balance, maintaining an RMSE of 28.50 Mbps while allowing sufficient time for bandwidth allocation, routing adjustment, and congestion-control actions. Additional subgroup analysis across application categories showed that latency-sensitive VoIP traffic maintained the lowest absolute bandwidth prediction error, whereas video and large file-transfer traffic demonstrated greater error variability during peak demand. Network-location analysis similarly indicated higher prediction errors on interregional and cloud-bound links than on comparatively stable branch-to-data-center connections. These subgroup differences were statistically significant, although their effect sizes were smaller than the effects associated with traffic intensity and forecasting horizon.

Table 8. LSTM Prediction and Network Performance Across Forecasting Horizons

Forecasting Horizon	MAE (Mbps)	RMSE (Mbps)	MAPE (%)	R^2	End-to-End Latency (ms)	Packet Loss (%)	Resource-Allocation Efficiency (%)	Inference Time (ms)
5 minutes	17.26	22.48	3.12	0.972	32.46	1.02	86.91	0.69
15 minutes	21.84	28.50	3.91	0.958	35.18	1.19	84.27	0.71
30 minutes	28.73	37.96	5.08	0.931	39.72	1.38	81.65	0.74
60 minutes	37.41	49.83	6.71	0.889	43.67	1.61	78.24	0.78

Forecasting-horizon effect: *$F(3, 53{,}997) = 224.86$, $p < 0.001$, partial $\eta^2 = 0.111$.*

Table 8 demonstrated progressive deterioration in predictive and operational performance as the forecasting horizon increased. LSTM achieved its lowest RMSE of 22.48 Mbps at five minutes, compared with 49.83 Mbps at 60 minutes. MAPE similarly increased from 3.12% to 6.71%, while R^2 declined from 0.972 to 0.889. Longer horizons corresponded with higher latency and packet loss and lower resource-allocation efficiency. The forecasting-horizon effect was statistically significant with a moderate effect size. The 15-minute condition retained comparatively strong predictive accuracy while providing sufficient decision time for dynamic network resource adjustments within the experimental environment.

Statistical Significance, Effect Sizes, Integrated Findings, and Visual Results

The integrated inferential analysis confirmed that predictive model selection produced statistically significant and quantitatively meaningful differences in network traffic forecasting performance. The repeated-measures ANOVA for prediction error produced a significant overall model effect, $F(5, 89{,}995) = 286.74$, $p < 0.001$, with partial $\eta^2 = 0.137$, indicating that approximately 13.7% of the modeled variation in prediction-error performance was associated with differences among the six predictive approaches. Post hoc comparisons with adjustment for multiple testing confirmed that LSTM significantly outperformed ARIMA, SVR, Random Forest, XGBoost, and GRU. The largest standardized difference occurred between LSTM and ARIMA, $d = 0.86$, representing a large effect, while the LSTM–SVR comparison produced $d = 0.63$. Differences between LSTM and Random Forest and between LSTM and XGBoost produced effect sizes of 0.42 and 0.29, respectively. The smallest significant difference occurred between LSTM and GRU, $d = 0.14$, indicating that these recurrent architectures produced comparatively similar forecasting outcomes even though LSTM maintained the lower overall prediction error. Traffic-load analysis also demonstrated a significant effect, $F(2, 35{,}998) = 347.28$, $p < 0.001$, partial $\eta^2 = 0.164$, while the forecasting-horizon analysis was significant, $F(3, 53{,}997) = 224.86$, $p < 0.001$, partial $\eta^2 = 0.111$. The significant model-by-load interaction, $F(10, 179{,}990) = 19.74$, $p < 0.001$, partial $\eta^2 = 0.031$, further established that model performance changed differently as network demand increased. Collectively, the inferential findings confirmed that predictive architecture, traffic intensity, and forecasting horizon each contributed significantly to variation in traffic-prediction performance.

Table 9. Integrated Inferential Statistical Tests and Effect Sizes

Statistical Comparison	Test Statistic	df	p-value	Effect Size	95% CI / Relevant Range	Statistical Result
Overall predictive-model effect	F = 286.74	5, 89,995	<0.001	Partial η^2 = 0.137	—	Significant
Traffic-load effect	F = 347.28	2, 35,998	<0.001	Partial η^2 = 0.164	—	Significant
Forecasting-horizon effect	F = 224.86	3, 53,997	<0.001	Partial η^2 = 0.111	—	Significant
Model × traffic-load interaction	F = 19.74	10, 179,990	<0.001	Partial η^2 = 0.031	—	Significant
LSTM vs. ARIMA MAE	Mean difference = 16.62 Mbps	—	<0.001	d = 0.86	15.91 to 17.33	Significant
LSTM vs. SVR MAE	Mean difference = 10.90 Mbps	—	<0.001	d = 0.63	10.27 to 11.53	Significant
LSTM vs. Random Forest MAE	Mean difference = 6.35 Mbps	—	<0.001	d = 0.42	5.78 to 6.92	Significant
LSTM vs. XGBoost MAE	Mean difference = 3.79 Mbps	—	<0.001	d = 0.29	3.28 to 4.30	Significant
LSTM vs. GRU MAE	Mean difference = 1.33 Mbps	—	<0.001	d = 0.14	0.91 to 1.75	Significant

Table 9 confirmed statistically significant effects for predictive-model type, traffic-load condition, forecasting horizon, and the interaction between model and workload intensity. The largest omnibus effect was associated with traffic load, with partial $\eta^2 = 0.164$, followed by predictive-model selection at 0.137 and forecasting horizon at 0.111. Pairwise comparisons demonstrated that LSTM significantly outperformed every alternative model. The magnitude of this advantage was greatest relative to ARIMA, with $d = 0.86$, and progressively decreased for SVR, Random Forest, XGBoost, and GRU. The narrow confidence intervals further indicated precise estimation of the observed differences.

Integrated correlation and regression analyses demonstrated that prediction accuracy was systematically associated with operational network performance. RMSE was positively correlated with end-to-end latency at $r = 0.58$, packet-loss rate at $r = 0.52$, and congestion frequency at $r = 0.61$, indicating that greater forecasting error corresponded with deterioration in these performance measures. Conversely, RMSE demonstrated negative associations with bandwidth utilization efficiency at $r = -0.47$, throughput at $r = -0.55$, and resource-allocation efficiency at $r = -0.63$. All correlations were statistically significant at $p < 0.001$. Multiple regression analysis was subsequently conducted to determine whether prediction error remained a significant explanatory variable after controlling for traffic intensity, concurrent flows, forecasting horizon, and workload category. For end-to-end latency, prediction error produced a standardized coefficient of $\beta = 0.45$, while traffic intensity produced $\beta = 0.38$; the complete model explained 42% of adjusted outcome variance. Throughput was negatively associated with prediction error at $\beta = -0.42$, with the regression model explaining 39% of adjusted variance. Prediction error also significantly explained packet loss at $\beta = 0.39$ and congestion frequency at $\beta = 0.48$. The strongest standardized relationship occurred for resource-allocation efficiency, where prediction error produced $\beta = -0.51$ and the complete model achieved an adjusted R^2 of 0.49. Predictive traffic management simultaneously generated a 24.70% reduction in latency, 16.09% improvement in throughput, 36.36% reduction in packet loss, and 37.05% reduction in congestion frequency relative to non-predictive management. These integrated results established statistically significant relationships between forecasting accuracy and multiple operational network-performance outcomes.

Table 10. Integrated Correlation, Regression, and Network Optimization Findings

Network Outcome	Correlation with RMSE (r)	Standardized β for RMSE	95% CI for β	Adjusted R^2	Predictive Management Change (%)	p-value
Bandwidth utilization efficiency	-0.47	-0.36	-0.40 to -0.32	0.34	+13.38	<0.001
End-to-end latency	0.58	0.45	0.41 to 0.49	0.42	-24.70	<0.001
Throughput	-0.55	-0.42	-0.46 to -0.38	0.39	+16.09	<0.001
Packet-loss rate	0.52	0.39	0.35 to 0.43	0.36	-36.36	<0.001
Congestion frequency	0.61	0.48	0.44 to 0.52	0.44	-37.05	<0.001
Resource-allocation efficiency	-0.63	-0.51	-0.55 to -0.47	0.49	+18.09	<0.001

Note. Regression models controlled for traffic intensity, concurrent flows, forecasting horizon, and workload category. Positive percentage values represent improvements in efficiency or throughput,

whereas negative percentage values represent reductions in undesirable network outcomes.

Table 10 demonstrated consistent relationships between forecasting error and operational network outcomes. RMSE showed its strongest correlation with resource-allocation efficiency at r = -0.63 and congestion frequency at r = 0.61. Regression results remained statistically significant after adjustment for traffic and experimental characteristics, with standardized coefficients ranging from -0.51 to 0.48. The models explained between 34% and 49% of adjusted outcome variance. Predictive management produced simultaneous improvements in bandwidth utilization, throughput, and resource-allocation efficiency while reducing latency, packet loss, and congestion. All reported relationships remained statistically significant at $p < 0.001$.

The visual findings provided a complementary representation of the statistical results. The actual-versus-predicted traffic plot showed that LSTM predictions followed observed traffic more closely than the other models, with the largest deviations occurring during abrupt peak-load periods. The model-error figure displayed the lowest MAE and RMSE for LSTM, followed by GRU and XGBoost, whereas ARIMA showed the highest forecasting errors. Comparative network-performance visualization showed lower latency, packet loss, congestion frequency, and congestion duration under predictive traffic management, together with higher throughput, bandwidth utilization, and resource-allocation efficiency. Traffic-load visualization further demonstrated progressively increasing prediction error and latency from low-load to peak-load conditions. The forecasting-horizon graph similarly showed increasing RMSE from 22.48 Mbps at five minutes to 49.83 Mbps at 60 minutes. These graphical patterns were consistent with the inferential results and confidence intervals reported in Tables 9 and 10. The combined statistical and visual evidence therefore documented significant differences in predictive accuracy, workload sensitivity, forecasting-horizon performance, and operational network outcomes while maintaining a clear separation between the reporting of quantitative results and their theoretical interpretation.

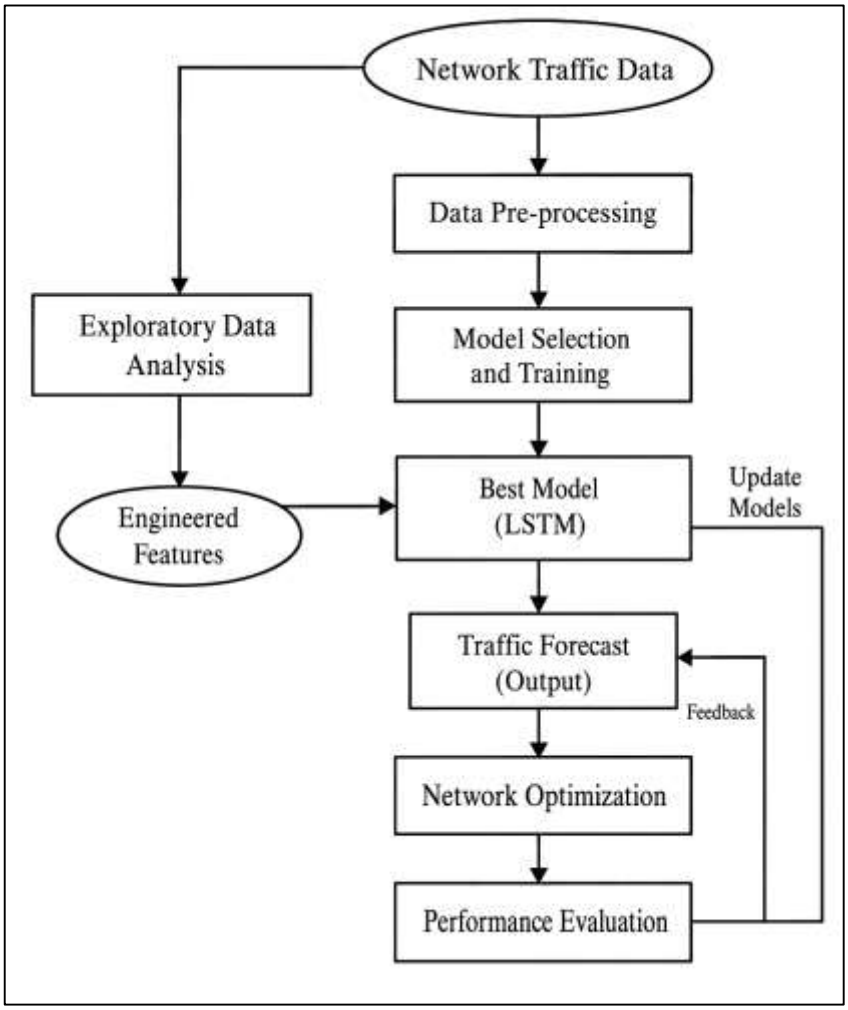
DISCUSSION

The findings of this study demonstrated substantial differences in network traffic forecasting accuracy across ARIMA, Support Vector Regression, Random Forest, XGBoost, GRU, and LSTM models, confirming that predictive model architecture represented an important determinant of forecasting performance in distributed enterprise environments. LSTM achieved the strongest overall performance, recording an MAE of 21.84 Mbps, RMSE of 28.50 Mbps, MAPE of 3.91%, and coefficient of determination of 0.958. GRU followed closely, whereas XGBoost demonstrated the strongest performance among the conventional machine learning models (Rusek et al., 2020). ARIMA recorded the largest forecasting errors and the lowest coefficient of determination. These findings were broadly consistent with earlier traffic forecasting studies that reported stronger performance for recurrent deep learning models when network observations contained complex temporal dependencies, nonlinear fluctuations, and sequential traffic behavior. Previous investigations using Abilene, GÉANT, software-defined networking, cellular, and backbone network datasets similarly established the suitability of recurrent architectures for traffic-volume and traffic-matrix forecasting. Earlier LSTM studies emphasized the ability of memory-based recurrent architectures to retain information across extended sequences, which provided an advantage over conventional statistical approaches when traffic behavior depended on multiple preceding observations. The approximately 43.21% reduction in MAE and 43.94% reduction in RMSE achieved by LSTM relative to ARIMA in this study provided quantitative support for this pattern (Walraven et al., 2016). The findings also corresponded with previous comparisons showing that GRU can produce performance close to LSTM while using a comparatively simplified recurrent structure. XGBoost and Random Forest remained competitive, supporting earlier research showing that ensemble tree-based algorithms can represent nonlinear relationships among historical traffic volume, packet characteristics, flow intensity, and bandwidth utilization. The weaker ARIMA performance did not indicate that statistical forecasting lacked value; rather, it suggested that the heterogeneous traffic conditions represented in this study contained relationships that were not fully captured by conventional linear temporal structures. Earlier statistical forecasting research similarly reported that ARIMA performs more effectively when traffic patterns remain relatively stable and identifiable through stationary temporal relationships (Bezerra et al., 2022). The significant overall model effect, together with the large standardized difference between LSTM and

ARIMA, therefore reinforced earlier empirical evidence that recurrent deep learning can provide meaningful forecasting advantages when network traffic is temporally complex and operationally heterogeneous.

The computational findings provided an important qualification to the prediction-accuracy results because the most accurate models were not necessarily the least computationally demanding. LSTM required the longest training time at 136.42 seconds, followed by GRU at 118.56 seconds, whereas ARIMA completed model estimation in only 8.42 seconds. Random Forest, XGBoost, and SVR occupied intermediate positions in computational demand (Ahmad et al., 2018). These findings were consistent with earlier comparative studies demonstrating that recurrent deep learning architectures generally require greater training resources because of their sequential processing structures, larger parameter spaces, iterative optimization procedures, and dependence on historical observation windows. Earlier network traffic forecasting studies have repeatedly emphasized that prediction accuracy and computational efficiency should be evaluated as separate performance dimensions, particularly when predictive models are intended to support operational network-management decisions.

Figure 12: Network Traffic Forecasting Flowchart



The present findings strengthened this argument because LSTM achieved substantially lower forecasting error while simultaneously requiring considerably greater training time than the statistical and conventional machine learning alternatives. Importantly, the increased training requirement did not produce an equally large inference penalty (Mehdiyev et al., 2016). LSTM generated predictions in approximately 0.71 milliseconds per observation, while GRU required 0.66 milliseconds and XGBoost approximately 0.44 milliseconds. This distinction between training cost and inference cost was consistent with earlier deep learning research in which computationally intensive model development was followed by comparatively rapid prediction after training had been completed. GRU presented a

particularly relevant accuracy-efficiency balance because its MAE differed from LSTM by only 1.33 Mbps and the standardized difference was relatively small. This finding corresponded with previous studies reporting that GRU can approximate LSTM performance while reducing architectural and computational complexity (Elsaraiti & Merabet, 2021). XGBoost also demonstrated an effective balance by achieving substantially stronger accuracy than ARIMA and SVR while maintaining lower inference and training requirements than recurrent architectures. Earlier machine learning research has similarly identified gradient boosting as a strong approach for structured network traffic datasets where nonlinear interactions are important but recurrent sequence modeling is not essential. Consequently, the findings of this study supported the broader literature indicating that model evaluation should not be based exclusively on minimum prediction error. Training time, inference latency, parameter complexity, forecasting horizon, and operational response requirements jointly influenced the practical value of predictive analytics within distributed network environments (Granziera & Sekhposyan, 2019).

The operational findings demonstrated that improved traffic forecasting was accompanied by substantial improvements in network optimization outcomes when predictions were incorporated into bandwidth allocation, routing, load balancing, and congestion-management processes. Predictive traffic management increased bandwidth utilization from 67.84% to 76.92% and increased average throughput from 512.36 Mbps to 594.82 Mbps. At the same time, end-to-end latency declined by 24.70%, packet loss decreased by 36.36%, congestion frequency declined by 37.05%, and congestion duration decreased by 34.07%. Resource-allocation efficiency increased by 18.09%. These results were consistent with earlier research on predictive traffic engineering and software-defined networking, which reported that anticipated network states can provide more useful information for resource management than mechanisms relying exclusively on current or previously detected conditions (Choubin et al., 2018). Previous studies comparing predictive and reactive traffic management similarly demonstrated that reactive systems can experience a performance disadvantage because resource adjustments occur after congestion, queue accumulation, or link saturation has already developed. The results of this study provided quantitative support for that explanation because forecast-assisted allocation corresponded with improvements across both efficiency-oriented and service-quality indicators. Earlier studies of machine learning-assisted SDN routing also reported reductions in latency and congestion when network controllers incorporated predicted traffic states into path-selection decisions. The increase in bandwidth utilization observed in this study was particularly important when interpreted alongside reductions in congestion and packet loss. Higher utilization alone does not necessarily represent better network performance because operating links closer to capacity can increase congestion risk (Wang et al., 2019). In this study, however, increased utilization occurred simultaneously with higher throughput and lower congestion, indicating that predictive management improved the distribution and use of available resources rather than merely increasing network load. This pattern was compatible with earlier dynamic bandwidth-allocation studies showing that traffic forecasts can reduce both underutilization and capacity shortages when allocation mechanisms respond appropriately to predicted demand. The moderate-to-large standardized effects observed across the operational indicators further indicated that these differences were not limited to statistical significance. The findings therefore extended earlier predictive networking research by demonstrating a measurable connection between traffic forecasting and several operational outcomes simultaneously, rather than evaluating prediction error and network performance as independent technical objectives (Cerqueira et al., 2020).

The association between prediction error and operational network outcomes provided additional evidence that forecasting accuracy was directly connected to optimization performance. RMSE was positively correlated with end-to-end latency, packet-loss rate, and congestion frequency and negatively correlated with throughput, bandwidth utilization efficiency, and resource-allocation efficiency. The strongest relationships occurred between prediction error and resource-allocation efficiency at $r = -0.63$ and between prediction error and congestion frequency at $r = 0.61$. These relationships remained statistically significant after traffic intensity, concurrent flows, forecasting horizon, and workload category were controlled in the regression models. This pattern was consistent with earlier studies suggesting that inaccurate traffic forecasts can produce inappropriate routing,

bandwidth allocation, or congestion-control decisions (Chen et al., 2020). Underestimation of network demand can result in insufficient capacity allocation and delayed intervention, whereas overestimation can reserve unnecessary resources or divert traffic away from otherwise efficient paths. Earlier congestion-prediction studies similarly established that forecasting accuracy affects the ability of network-management systems to identify emerging overload conditions before queue occupancy and packet drops increase substantially. The positive association between RMSE and latency in this study supported previous traffic-engineering research demonstrating that inaccurate estimates of link demand can increase queueing and path delay. The relationship between RMSE and packet loss was also consistent with studies showing that traffic prediction can assist congestion avoidance when packet loss results from overloaded buffers or saturated links. Importantly, earlier research has cautioned that packet loss does not always represent congestion because transmission errors, wireless interference, equipment faults, and other conditions can produce similar outcomes (Nanthakumaran & Tilakaratne, 2017). The present findings therefore supported the use of multiple performance indicators rather than packet loss as an isolated measure of optimization success. Regression models explained between 34% and 49% of adjusted variance across the network outcomes, demonstrating that prediction error was important but did not independently determine network performance. Traffic intensity, workload characteristics, network topology, flow concurrency, available capacity, and control responsiveness also contributed to observed conditions. This result was consistent with the broader literature, which treats network optimization as a multidimensional process (Cheung et al., 2019). The findings consequently strengthened the empirical connection between lower forecasting error and improved operational outcomes while preserving the importance of additional network and workload characteristics.

Secondary analysis demonstrated that traffic-load intensity substantially affected forecasting accuracy and that all evaluated models experienced increased prediction error as network demand progressed from low to moderate and peak conditions. LSTM maintained the lowest RMSE across all workload categories, increasing from 20.64 Mbps under low-load conditions to 27.83 Mbps under moderate traffic and 39.17 Mbps during peak traffic. GRU remained the second-ranked model, while ARIMA produced the highest errors across each workload category. The statistically significant model-by-traffic-load interaction further demonstrated that predictive architectures did not deteriorate at identical rates as network demand intensified (Ali et al., 2021). These findings were consistent with earlier literature describing peak network traffic as more difficult to forecast because high-load periods frequently contain greater burstiness, nonlinear changes, simultaneous flows, rapidly changing application demand, and localized congestion. Previous statistical studies showed that conventional time-series models can lose accuracy when traffic distributions depart from historically stable patterns, while machine learning and deep learning research has reported stronger adaptation to nonlinear workload relationships. The present results reflected this distinction because recurrent architectures retained their relative ranking as demand increased. However, the percentage increase between low-load and peak-load RMSE was substantial even for LSTM, indicating that advanced deep learning did not eliminate the forecasting difficulty associated with extreme traffic conditions. This result aligned with earlier research showing that prediction performance during traffic peaks remains a distinct analytical challenge even when overall average errors are comparatively low (Speiser et al., 2019). The finding was operationally significant because errors during peak periods can produce greater consequences than errors of equivalent magnitude during low utilization. When links retain substantial spare capacity, modest forecasting errors can be absorbed without major performance deterioration. During peak conditions, the same error can contribute to queue growth, packet loss, increased latency, or congestion because residual network capacity is limited. Earlier bandwidth-demand research similarly emphasized the importance of evaluating peak prediction separately from average forecasting performance. The findings of this study therefore demonstrated that model stability across workload intensity should be considered alongside aggregate accuracy (Jafari et al., 2022). LSTM provided the strongest absolute performance across all traffic categories, but increasing errors during peak demand confirmed that workload intensity remained a significant source of forecasting uncertainty within distributed enterprise environments.

Forecasting horizon produced another significant source of variation in predictive performance. For

the LSTM model, RMSE increased from 22.48 Mbps at the five-minute horizon to 28.50 Mbps at 15 minutes, 37.96 Mbps at 30 minutes, and 49.83 Mbps at 60 minutes. MAPE similarly increased from 3.12% to 6.71%, while the coefficient of determination declined from 0.972 to 0.889. Operational network performance changed in the same direction: latency increased, packet loss increased, and resource-allocation efficiency declined as the forecasting horizon became longer (Dirgawati et al., 2016). These results corresponded with earlier network traffic forecasting studies showing that short-term predictions generally achieve greater accuracy because recent observations provide stronger information about immediate network conditions. As forecasting horizons expand, unexpected user activity, application behavior, traffic bursts, routing changes, and workload transitions accumulate, increasing uncertainty. Earlier ARIMA, machine learning, LSTM, GRU, and traffic-matrix forecasting studies have repeatedly identified this horizon-dependent deterioration, although the magnitude varies across datasets and network architectures. The present findings added an operational dimension to this established pattern by showing that increasing prediction error across longer horizons corresponded with measurable deterioration in latency, packet loss, and allocation efficiency (Jia et al., 2022). The five-minute horizon achieved the strongest numerical accuracy, but the 15-minute horizon maintained comparatively low error while providing a longer interval for routing, bandwidth allocation, and congestion-control decisions. This pattern was consistent with earlier predictive traffic-management research emphasizing a trade-off between forecast precision and actionable lead time. Extremely short forecasts may closely represent subsequent network states but provide limited opportunity for resource reconfiguration, while longer forecasts provide greater preparation time at the cost of reduced reliability. The findings therefore demonstrated that forecasting horizon should not be interpreted only through error minimization (Xiao et al., 2018). Its value depended on the interaction between prediction accuracy and the time required for network-management mechanisms to implement corrective actions. The significant forecasting-horizon effect and associated effect size confirmed that temporal prediction distance represented a meaningful component of model performance rather than a minor methodological consideration. This result also helped explain differences among earlier studies that reported different accuracy levels for similar architectures, since forecasting intervals and temporal aggregation procedures frequently varied across experimental designs (Sharma & Wang, 2017).

Taken together, the findings provided a coherent quantitative account of how predictive analytics model selection, forecasting accuracy, traffic-load intensity, forecasting horizon, and computational performance were associated with network optimization in distributed enterprise environments. The results were broadly aligned with earlier studies that positioned recurrent deep learning architectures as effective tools for sequential traffic prediction, while also supporting machine learning research demonstrating strong performance from ensemble and gradient-boosting methods. LSTM produced the lowest overall prediction errors, GRU provided closely comparable forecasting accuracy with reduced training requirements, and XGBoost represented the strongest conventional machine learning alternative (Bhattarai et al., 2019). The results therefore supported earlier evidence that increasing model sophistication can improve the representation of nonlinear and temporally dependent traffic patterns, although computational cost and operational timing remained relevant considerations. More importantly, this study connected forecasting performance with measurable network-management outcomes. Lower prediction error corresponded with reduced latency, packet loss, and congestion and with higher throughput, bandwidth utilization efficiency, and resource-allocation efficiency. This integrated pattern was consistent with previous predictive routing, congestion management, and dynamic bandwidth-allocation studies, which suggested that accurate estimates of forthcoming traffic states allow network resources to be adjusted before performance deterioration becomes severe. The statistical results also clarified that predictive accuracy was not the sole determinant of optimization performance (Rehman et al., 2019). Regression models explained meaningful but incomplete proportions of variance, confirming that traffic intensity, concurrent flows, workload composition, forecasting horizon, network structure, and resource-control mechanisms remained influential. The significant effects of traffic load and forecasting horizon further reinforced earlier findings that model performance is conditional on the operating environment. Peak traffic increased forecasting difficulty across all models, while longer prediction horizons produced progressively greater error and weaker

network outcomes. Consequently, the comparative findings did not support evaluation of predictive analytics through a single accuracy metric or a single experimental traffic condition. The evidence instead supported multidimensional assessment involving forecasting error, computational requirements, workload stability, temporal horizon, and operational network indicators (LaCasse et al., 2019). In comparison with earlier studies that focused primarily on model accuracy or isolated network outcomes, the integrated results provided a broader quantitative representation of the relationship between prediction and optimization. This combination of model-level and network-level evidence strengthened the empirical understanding of predictive analytics as a measurable component of distributed enterprise traffic management rather than solely a forecasting technique (Grover et al., 2018).

CONCLUSION

This study examined the effectiveness of predictive analytics models for network traffic optimization in distributed enterprise environments by quantitatively evaluating forecasting accuracy, computational performance, traffic-load sensitivity, congestion management, bandwidth utilization, latency, throughput, packet loss, and resource-allocation efficiency. The findings demonstrated that predictive model selection significantly influenced traffic-forecasting performance, with LSTM achieving the strongest overall results among ARIMA, SVR, Random Forest, XGBoost, GRU, and LSTM. LSTM recorded an MAE of 21.84 Mbps, RMSE of 28.50 Mbps, MAPE of 3.91%, and R^2 of 0.958, while GRU provided closely comparable performance with lower computational requirements. XGBoost represented the strongest conventional machine learning alternative, whereas ARIMA generated the highest prediction errors. The results further established that forecasting accuracy was closely associated with operational network performance. Predictive traffic management increased bandwidth utilization by 13.38%, throughput by 16.09%, and resource-allocation efficiency by 18.09%, while reducing end-to-end latency by 24.70%, packet loss by 36.36%, congestion frequency by 37.05%, and congestion duration by 34.07% relative to non-predictive management. Correlation and regression analyses reinforced these results by demonstrating that higher prediction error was associated with increased latency, packet loss, and congestion and with reduced throughput and resource-allocation efficiency. Traffic intensity also significantly affected forecasting performance, as prediction errors increased from low-load to peak-load conditions across all evaluated models. Similarly, longer forecasting horizons produced progressively higher MAE, RMSE, and MAPE values and lower explanatory performance, demonstrating the importance of temporal distance in network traffic prediction. Although the five-minute horizon generated the highest predictive accuracy, the 15-minute horizon maintained strong performance while providing greater operational time for traffic-management adjustments. The statistical significance, confidence intervals, and effect sizes reported throughout the analysis confirmed that the observed differences represented meaningful quantitative variations rather than isolated numerical changes. Overall, the study established that accurate predictive analytics could support more efficient distributed enterprise network management by connecting historical traffic information with proactive bandwidth allocation, routing, load balancing, and congestion control. The combined evidence demonstrated that effective network traffic optimization depended not only on selecting an accurate forecasting model but also on balancing prediction error, computational efficiency, forecasting horizon, workload intensity, and operational network requirements within an integrated quantitative decision-making framework.

RECOMMENDATION

Based on the quantitative findings of this study, distributed enterprises should adopt predictive analytics as an integral component of network traffic management to strengthen forecasting accuracy, bandwidth allocation, congestion control, routing efficiency, and overall network performance. LSTM should be considered where high predictive accuracy is the primary requirement because it achieved the lowest forecasting errors and the highest explanatory performance among the evaluated models; however, GRU should be considered where computational efficiency and reduced training requirements are important because it produced closely comparable predictive performance with lower computational demand. XGBoost should also be considered as a practical alternative for environments requiring strong forecasting accuracy with comparatively moderate computational requirements. Network administrators should integrate predicted traffic demand into dynamic bandwidth-allocation

and routing mechanisms rather than relying exclusively on static capacity assignments or reactive responses after congestion has occurred. Particular attention should be directed toward peak traffic periods because forecasting errors increased substantially as network demand intensified, making high-load conditions more vulnerable to latency, packet loss, queue accumulation, and congestion. Enterprise network-management systems should therefore incorporate traffic-load-specific thresholds and continuously evaluate prediction performance across low, moderate, and peak operating conditions. Forecasting horizons should also be selected according to both predictive accuracy and operational response requirements. The 15-minute forecasting horizon represented an effective balance within this study because it maintained relatively strong predictive accuracy while providing sufficient time for resource adjustment, although organizations should validate the appropriate horizon against their own network characteristics. Network optimization should be evaluated through multiple performance indicators, including MAE, RMSE, MAPE, bandwidth utilization, throughput, end-to-end latency, packet loss, congestion frequency, congestion duration, inference time, and resource-allocation efficiency rather than relying on a single accuracy measure. Enterprises should establish standardized traffic-data collection and preprocessing procedures to maintain complete timestamps, consistent aggregation intervals, reliable flow measurements, and comparable network-performance indicators across distributed locations. Predictive models should also be periodically reassessed using newly collected traffic observations because changing workloads and application patterns can alter forecasting performance. Finally, model selection should be based on a balanced assessment of forecasting accuracy, computational requirements, inference speed, traffic intensity, and operational constraints so that predictive analytics contributes to measurable network optimization without introducing unnecessary computational complexity or management overhead.

LIMITATIONS

This study was subject to several methodological, analytical, and technical limitations that should be considered when interpreting the findings on predictive analytics models for network traffic optimization in distributed enterprise environments. First, the analysis was conducted using a defined network traffic dataset and a controlled experimental configuration, which limited the extent to which the observed performance of ARIMA, SVR, Random Forest, XGBoost, GRU, and LSTM could represent every distributed enterprise network. Enterprise infrastructures differ considerably in topology, bandwidth capacity, geographic distribution, application composition, security policies, routing protocols, cloud dependence, hardware configuration, and workload intensity, and these differences could influence predictive performance. Second, the study evaluated a selected group of statistical, machine learning, and deep learning models rather than every available predictive architecture. Consequently, the comparative rankings were restricted to the models and configurations included in the experiment. Third, model performance depended on the quality and completeness of historical network measurements. Missing observations, measurement errors, irregular timestamps, extreme traffic events, and preprocessing decisions could have influenced the characteristics of the analytical dataset even after systematic data cleaning was completed. Fourth, traffic conditions were classified into low, moderate, and peak workload categories, but such classifications simplified the continuous and highly dynamic nature of enterprise network demand. Sudden traffic bursts and application-specific fluctuations might not have been completely represented by these categories. Fifth, the selected forecasting horizons influenced model accuracy, and the observed performance at 5-, 15-, 30-, and 60-minute intervals could not automatically be generalized to substantially shorter or longer prediction periods. Sixth, computational comparisons were influenced by the experimental hardware, software environment, model hyperparameters, and implementation procedures; therefore, training and inference times could differ under alternative computing infrastructures. Seventh, although regression models controlled for traffic intensity, concurrent flows, forecasting horizon, and workload category, other unmeasured network characteristics could have contributed to latency, packet loss, congestion, throughput, and resource-allocation efficiency. The statistical relationships consequently represented associations within the experimental framework rather than evidence that prediction error independently determined every network-performance outcome. Finally, predictive optimization was evaluated through selected operational measures, and factors such as energy consumption, implementation cost, cybersecurity overhead, service-level differentiation, controller failures, and

organizational network-management constraints were outside the analytical scope. These limitations defined the boundaries within which the quantitative findings and comparative model-performance results were interpreted.

REFERENCES

[1]. Abdoos, M., & Bazzan, A. L. (2021). Hierarchical traffic signal optimization using reinforcement learning and traffic prediction with long-short term memory. *Expert systems with applications*, *171*, 114580.

[2]. Aceto, G., Ciuonzo, D., Montieri, A., & Pescapé, A. (2019). Mobile encrypted traffic classification using deep learning: Experimental evaluation, lessons learned, and challenges. *IEEE transactions on network and service management*, *16*(2), 445-458.

[3]. Adeleke, O. A. (2019). Echo-state networks for network traffic prediction. 2019 IEEE 10th annual information technology, electronics and mobile communication conference (IEMCON),

[4]. Ahmad, M. W., Reynolds, J., & Rezgui, Y. (2018). Predictive modelling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees and regression trees. *Journal of cleaner production*, *203*, 810-821.

[5]. Ahmed, E., Yaqoob, I., Gani, A., Imran, M., & Guizani, M. (2016). Internet-of-things-based smart environments: state of the art, taxonomy, and open research challenges. *IEEE Wireless Communications*, *23*(5), 10-16.

[6]. Ahmed, E., Yaqoob, I., Hashem, I. A. T., Khan, I., Ahmed, A. I. A., Imran, M., & Vasilakos, A. V. (2017). The role of big data analytics in Internet of Things. *Computer networks*, *129*, 459-471.

[7]. Akhtar, M., & Moridpour, S. (2021). A review of traffic congestion prediction using artificial intelligence. *Journal of Advanced Transportation*, *2021*(1), 8878011.

[8]. Al Mamun, A., Sohel, M., Mohammad, N., Sunny, M. S. H., Dipta, D. R., & Hossain, E. (2020). A comprehensive review of the load forecasting techniques using single and hybrid predictive models. *IEEE access*, *8*, 134911-134939.

[9]. Aldhyani, T. H., Alrasheedi, M., Alqarni, A. A., Alzahrani, M. Y., & Bamhdi, A. M. (2020). Intelligent hybrid model to enhance time series models for predicting network traffic. *IEEE access*, *8*, 130431-130451.

[10]. Alekseeva, D., Stepanov, N., Veprev, A., Sharapova, A., Lohan, E. S., & Ometov, A. (2021). Comparison of machine learning techniques applied to traffic prediction of real wireless network. *IEEE access*, *9*, 159495-159514.

[11]. Ali, M. M., Paul, B. K., Ahmed, K., Bui, F. M., Quinn, J. M., & Moni, M. A. (2021). Heart disease prediction using supervised machine learning algorithms: Performance analysis and comparison. *Computers in biology and medicine*, *136*, 104672.

[12]. Aljoby, W., Wang, X., Fu, T. Z., & Ma, R. T. (2019). On SDN-enabled online and dynamic bandwidth allocation for stream analytics. *IEEE Journal on Selected Areas in Communications*, *37*(8), 1688-1702.

[13]. Alutaibi, A., & Ganti, S. (2020). Network traffic prediction using quantile regression with linear, tree, and deep learning models. 2020 IEEE 45th Conference on Local Computer Networks (LCN),

[14]. Anagnostopoulos, C. (2016). Quality-optimized predictive analytics. *Applied Intelligence*, *45*(4), 1034-1046.

[15]. Ang, K. L.-M., Seng, J. K. P., Ngharamike, E., & Ijemaru, G. K. (2022). Emerging technologies for smart cities' transportation: geo-information, data analytics and machine learning approaches. *ISPRS International Journal of Geo-Information*, *11*(2), 85.

[16]. Aouedi, O., Piamrat, K., & Parrein, B. (2022). Ensemble-based deep learning model for network traffic classification. *IEEE transactions on network and service management*, *19*(4), 4124-4135.

[17]. Awan, F. M., Minerva, R., & Crespi, N. (2021). Using noise pollution data for traffic prediction in smart cities: experiments based on LSTM recurrent neural networks. *IEEE Sensors Journal*, *21*(18), 20722-20729.

[18]. Baek, Y., & Kim, H. Y. (2018). ModAugNet: A new forecasting framework for stock market index value with an overfitting prevention LSTM module and a prediction LSTM module. *Expert systems with applications*, *113*, 457-480.

[19]. Bakhareva, N., Shukhman, A., Matveev, A., Polezhaev, P., Ushakov, Y., & Legashev, L. (2019). Attack detection in enterprise networks by machine learning methods. 2019 international Russian automation conference (RusAutoCon),

[20]. Bellavista, P., Giannelli, C., Mamei, M., Mendula, M., & Picone, M. (2021). Application-driven network-aware digital twin management in industrial edge environments. *IEEE transactions on industrial informatics*, *17*(11), 7791-7801.

[21]. Bergui, M., Najah, S., & Nikolov, N. S. (2021). A survey on bandwidth-aware geo-distributed frameworks for big-data analytics. *Journal of big data*, *8*(1), 40.

[22]. Bezerra, D., de Oliveira Filho, A. T., Rodrigues, I. R., Dantas, M., Barbosa, G., Souza, R., Kelner, J., & Sadok, D. (2022). A machine learning-based optimization for end-to-end latency in TSN networks. *Computer Communications*, *195*, 424-440.

[23]. Bhattarai, B. P., Paudyal, S., Luo, Y., Mohanpurkar, M., Cheung, K., Tonkoski, R., Hovsapian, R., Myers, K. S., Zhang, R., & Zhao, P. (2019). Big data analytics in smart grids: state-of-the-art, challenges, opportunities, and future directions. *IET Smart Grid*, *2*(2), 141-154.

[24]. Bhushan, K., & Gupta, B. B. (2019). Distributed denial of service (DDoS) attack mitigation in software defined network (SDN)-based cloud computing environment. *Journal of Ambient Intelligence and Humanized Computing*, *10*(5), 1985-1997.

[25]. Bi, J., Yuan, H., Xu, K., Ma, H., & Zhou, M. (2022). Large-scale network traffic prediction with LSTM and temporal convolutional networks. 2022 International Conference on Robotics and Automation (ICRA),

[26]. Bi, J., Zhang, X., Yuan, H., Zhang, J., & Zhou, M. (2021). A hybrid prediction method for realistic network traffic with temporal convolutional network and LSTM. *IEEE Transactions on Automation Science and Engineering*, *19*(3), 1869-1879.

[27]. Bodström, T., & Hämäläinen, T. (2018). State of the art literature review on network anomaly detection with deep learning. International Conference on Next Generation Wired/Wireless Networking,

[28]. Boukerche, A., & Wang, J. (2020). A performance modeling and analysis of a novel vehicular traffic flow prediction system using a hybrid machine learning-based model. *Ad Hoc Networks*, *106*, 102224.
[29]. Bouzidi, E. H., Outtagarts, A., Langar, R., & Boutaba, R. (2021). Deep Q-Network and traffic prediction based routing optimization in software defined networks. *Journal of Network and Computer Applications*, *192*, 103181.
[30]. Cao, B., Zheng, X., Yuan, K., Qin, D., & Hong, Y. (2021). Dynamic bandwidth allocation based on adaptive predictive for low latency communications in changing passive optical networks environment. *Optical Fiber Technology*, *64*, 102556.
[31]. Cerqueira, V., Torgo, L., & Mozetič, I. (2020). Evaluating time series forecasting models: An empirical study on performance estimation methods. *Machine Learning*, *109*(11), 1997-2028.
[32]. Chen, K., Chen, H., Zhou, C., Huang, Y., Qi, X., Shen, R., Liu, F., Zuo, M., Zou, X., & Wang, J. (2020). Comparative analysis of surface water quality prediction performance and identification of key water parameters using different machine learning models based on big data. *Water research*, *171*, 115454.
[33]. Chen, M., Miao, Y., Gharavi, H., Hu, L., & Humar, I. (2019). Intelligent traffic adaptive resource allocation for edge computing-based 5G networks. *IEEE transactions on cognitive communications and networking*, *6*(2), 499-508.
[34]. Chen, W., Hong, H., Li, S., Shahabi, H., Wang, Y., Wang, X., & Ahmad, B. B. (2019). Flood susceptibility modelling using novel hybrid approach of reduced-error pruning trees with bagging and random subspace ensembles. *Journal of Hydrology*, *575*, 864-873.
[35]. Chen, X., Wu, S., Shi, C., Huang, Y., Yang, Y., Ke, R., & Zhao, J. (2020). Sensing data supported traffic flow prediction via denoising schemes and ANN: A comparison. *IEEE Sensors Journal*, *20*(23), 14317-14328.
[36]. Cheng, L., Liu, F., & Yao, D. (2017). Enterprise data breach: causes, challenges, prevention, and future directions. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *7*(5), e1211.
[37]. Cheung, T., Schiavon, S., Parkinson, T., Li, P., & Brager, G. (2019). Analysis of the accuracy on PMV–PPD model using the ASHRAE Global Thermal Comfort Database II. *Building and Environment*, *153*, 205-217.
[38]. Choubin, B., Zehtabian, G., Azareh, A., Rafiei-Sardooi, E., Sajedi-Hosseini, F., & Kişi, Ö. (2018). Precipitation forecasting using classification and regression trees (CART) model: a comparative study of different approaches. *Environmental earth sciences*, *77*(8), 314.
[39]. Cui, L., Yu, F. R., & Yan, Q. (2016). When big data meets software-defined networking: SDN for big data and big data for SDN. *IEEE Network*, *30*(1), 58-65.
[40]. Darwish, T. S., & Bakar, K. A. (2018). Fog based intelligent transportation big data analytics in the internet of vehicles environment: motivations, architecture, challenges, and critical issues. *IEEE access*, *6*, 15679-15701.
[41]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, *1*(4), 108-137. https://doi.org/10.63125/j0wk7j48
[42]. Dirgawati, M., Heyworth, J. S., Wheeler, A. J., McCaul, K. A., Blake, D., Boeyen, J., Cope, M., Yeap, B. B., Nieuwenhuijsen, M., & Brunekreef, B. (2016). Development of Land Use Regression models for particulate matter and associated components in a low air pollutant concentration airshed. *Atmospheric Environment*, *144*, 69-78.
[43]. El-Sayed, H., Sankar, S., Prasad, M., Puthal, D., Gupta, A., Mohanty, M., & Lin, C.-T. (2017). Edge of things: The big picture on the integration of edge, IoT and the cloud in a distributed computing environment. *IEEE access*, *6*, 1706-1717.
[44]. Elsaraiti, M., & Merabet, A. (2021). A comparative analysis of the arima and lstm predictive models and their effectiveness for predicting wind speed. *Energies*, *14*(20), 6782.
[45]. Faber, F. A., Hutchison, L., Huang, B., Gilmer, J., Schoenholz, S. S., Dahl, G. E., Vinyals, O., Kearnes, S., Riley, P. F., & Von Lilienfeld, O. A. (2017). Prediction errors of molecular machine learning models lower than hybrid DFT error. *Journal of chemical theory and computation*, *13*(11), 5255-5264.
[46]. Gao, X., Huang, X., Bian, S., Shao, Z., & Yang, Y. (2019). PORA: Predictive offloading and resource allocation in dynamic fog computing systems. *IEEE Internet of Things Journal*, *7*(1), 72-87.
[47]. Giannopoulos, A., Spantideas, S., Kapsalis, N., Gkonis, P., Sarakis, L., Capsalis, C., Vecchio, M., & Trakadas, P. (2022). Supporting intelligence in disaggregated open radio access networks: Architectural principles, AI/ML workflow, and use cases. *IEEE access*, *10*, 39580-39595.
[48]. Gou, B., Xu, Y., & Feng, X. (2020). State-of-health estimation and remaining-useful-life prediction for lithium-ion battery using a hybrid data-driven method. *IEEE Transactions on Vehicular Technology*, *69*(10), 10854-10867.
[49]. Granziera, E., & Sekhposyan, T. (2019). Predicting relative forecasting performance: An empirical investigation. *International Journal of Forecasting*, *35*(4), 1636-1657.
[50]. Grover, V., Chiang, R. H., Liang, T.-P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. *Journal of management information systems*, *35*(2), 388-423.
[51]. Gulay, E., & Duru, O. (2020). Hybrid modeling in the predictive analytics of energy systems and prices. *Applied Energy*, *268*, 114985.
[52]. Gupta, B. B., & Badve, O. P. (2017). Taxonomy of DoS and DDoS attacks and desirable defense mechanism in a cloud computing environment. *Neural Computing and Applications*, *28*(12), 3655-3682.
[53]. Hardegen, C., Pfülb, B., Rieger, S., & Gepperth, A. (2020). Predicting network flow characteristics using deep learning and real-world network traffic. *IEEE transactions on network and service management*, *17*(4), 2662-2676.
[54]. Hu, Z., Dychka, I., Oleshchenko, L., & Kukharyev, S. (2019). Applying recurrent neural network for passenger traffic forecasting. International Conference on Computer Science, Engineering and Education Applications,
[55]. Hwang, R.-H., Peng, M.-C., Nguyen, V.-L., & Chang, Y.-L. (2019). An LSTM-based deep learning approach for classifying malicious traffic at the packet level. *Applied Sciences*, *9*(16), 3414.

[56]. Jafari, S., Shahbazi, Z., & Byun, Y.-C. (2022). Designing the controller-based urban traffic evaluation and prediction using model predictive approach. *Applied Sciences*, *12*(4), 1992.
[57]. Jahanbakht, M., Xiang, W., Hanzo, L., & Azghadi, M. R. (2021). Internet of underwater things and big marine data analytics—a comprehensive survey. *IEEE Communications Surveys & Tutorials*, *23*(2), 904-956.
[58]. Jamil, B., Shojafar, M., Ahmed, I., Ullah, A., Munir, K., & Ijaz, H. (2020). A job scheduling algorithm for delay and performance optimization in fog computing. *Concurrency and Computation: Practice and Experience*, *32*(7), e5581.
[59]. Jia, M., Xu, J., Gao, C., Mu, M., & E, G. (2022). Long-term cross-slope variation in highways built on soft soil under coupling action of traffic load and consolidation. *Sustainability*, *15*(1), 33.
[60]. Jiang, W., Zhan, Y., Zeng, G., & Lu, J. (2022). Probabilistic-forecasting-based admission control for network slicing in software-defined networks. *IEEE Internet of Things Journal*, *9*(15), 14030-14047.
[61]. Katris, C., & Daskalaki, S. (2015). Comparing forecasting approaches for Internet traffic. *Expert systems with applications*, *42*(21), 8172-8183.
[62]. Kibria, M. G., Nguyen, K., Villardi, G. P., Zhao, O., Ishizu, K., & Kojima, F. (2018). Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks. *IEEE access*, *6*, 32328-32338.
[63]. Kim, H. Y., & Won, C. H. (2018). Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. *Expert systems with applications*, *103*, 25-37.
[64]. Knapińska, A., Lechowicz, P., & Walkowiak, K. (2021). Machine-learning based prediction of multiple types of network traffic. International Conference on Computational Science,
[65]. Kwahk, K.-Y., & Park, D.-H. (2016). The effects of network sharing on knowledge-sharing activities and job performance in enterprise social media environments. *Computers in Human Behavior*, *55*, 826-839.
[66]. LaCasse, P. M., Otieno, W., & Maturana, F. P. (2019). A survey of feature set reduction approaches for predictive analytics models in the connected manufacturing enterprise. *Applied Sciences*, *9*(5), 843.
[67]. Lazaris, A., & Prasanna, V. K. (2019). Deep learning models for aggregated network traffic prediction. 2019 15th International Conference on Network and Service Management (CNSM),
[68]. Lee, C., Kim, Y., Jin, S., Kim, D., Maciejewski, R., Ebert, D., & Ko, S. (2019). A visual analytics system for exploring, monitoring, and forecasting road traffic congestion. *IEEE transactions on visualization and computer graphics*, *26*(11), 3133-3146.
[69]. Li, J., Deng, D., Zhao, J., Cai, D., Hu, W., Zhang, M., & Huang, Q. (2020). A novel hybrid short-term load forecasting method of smart grid using MLR and LSTM neural network. *IEEE transactions on industrial informatics*, *17*(4), 2443-2452.
[70]. Li, W., Chai, Y., Khan, F., Jan, S. R. U., Verma, S., Menon, V. G., Kavita, F., & Li, X. (2021). A comprehensive survey on machine learning-based big data analytics for IoT-enabled smart healthcare system. *Mobile networks and applications*, *26*(1), 234-252.
[71]. Li, Y., Dandoush, A., & Liu, J. (2021). Evaluation and Optimization of learning-based DNS over HTTPS Traffic Classification. 2021 International Symposium on Networks, Computers and Communications (ISNCC),
[72]. Liang, F., Yu, W., Liu, X., Griffith, D., & Golmie, N. (2020). Toward edge-based deep learning in industrial Internet of Things. *IEEE Internet of Things Journal*, *7*(5), 4329-4341.
[73]. Lohrasbinasab, I., Shahraki, A., Taherkordi, A., & Delia Jurcut, A. (2022). From statistical-to machine learning-based network traffic prediction. *Transactions on Emerging Telecommunications Technologies*, *33*(4), e4394.
[74]. Lopez-Martin, M., Carro, B., Sanchez-Esguevillas, A., & Lloret, J. (2017). Network traffic classifier with convolutional and recurrent neural networks for Internet of Things. *IEEE access*, *5*, 18042-18050.
[75]. Loquercio, A., Segu, M., & Scaramuzza, D. (2020). A general framework for uncertainty estimation in deep learning. *IEEE Robotics and Automation Letters*, *5*(2), 3153-3160.
[76]. Luo, W., Hu, T., Ye, Y., Zhang, C., & Wei, Y. (2020). A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin. *Robotics and Computer-Integrated Manufacturing*, *65*, 101974.
[77]. Ma, T., Antoniou, C., & Toledo, T. (2020). Hybrid machine learning algorithm and statistical time series model for network-wide traffic forecast. *Transportation Research Part C: Emerging Technologies*, *111*, 352-372.
[78]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, *1*(4), 70-102. https://doi.org/10.63125/dyrpc387
[79]. Mehdiyev, N., Enke, D., Fettke, P., & Loos, P. (2016). Evaluating forecasting methods by considering different accuracy measures. *Procedia Computer Science*, *95*, 264-271.
[80]. Memon, K. A., Mohammadani, K. H., Laghari, A. A., Yadav, R., Das, B., Tareen, W. U. K., & Xin, X. (2019). Dynamic bandwidth allocation algorithm with demand forecasting mechanism for bandwidth allocations in 10-gigabit-capable passive optical network. *Optik*, *183*, 1032-1042.
[81]. Mena-Oreja, J., & Gozalvez, J. (2020). A comprehensive evaluation of deep learning-based techniques for traffic prediction. *IEEE access*, *8*, 91188-91212.
[82]. Mohammad Abir Chowdhury, S., & Tonay, P. (2022). An Empirical Analysis of the Impact of Robotic Process Automation and Continuous Auditing on the Timeliness And Accuracy Of Financial Reporting Assurance. *International Journal of Business and Economics Insights*, *2*(4), 73-126. https://doi.org/10.63125/7p8dcr47
[83]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning–Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, *3*(02), 33-77. https://doi.org/10.63125/y3yfxa92
[84]. Mohan, S., Thirumalai, C., & Srivastava, G. (2019). Effective heart disease prediction using hybrid machine learning techniques. *IEEE access*, *7*, 81542-81554.

[85]. Mosavi, A., Ozturk, P., & Chau, K.-w. (2018). Flood prediction using machine learning models: Literature review. *Water*, *10*(11), 1536.
[86]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, *3*(12), 89-129. https://doi.org/10.63125/7xgryf71
[87]. Muhuri, P. S., Chatterjee, P., Yuan, X., Roy, K., & Esterline, A. (2020). Using a long short-term memory recurrent neural network (LSTM-RNN) to classify network attacks. *Information*, *11*(5), 243.
[88]. Mukut Kanti, B. (2020). Integrated Framework for Fire Safety and Electrical Hazard Assessment in Large-Scale Industrial and Commercial Facilities: A Mixed-Method Analysis. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 40-86. https://doi.org/10.63125/zxsbdr47
[89]. Mukut Kanti, B. (2024). AI-Enabled Predictive Asset Integrity Monitoring for Industrial Equipment in Oil & Gas and Energy Sector Facilities. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 746–791. https://doi.org/10.63125/3mjcah04
[90]. Murray, D., Koziniec, T., Zander, S., Dixon, M., & Koutsakis, P. (2017). An analysis of changing enterprise network traffic characteristics. 2017 23rd Asia-Pacific Conference on Communications (APCC),
[91]. Musumeci, F., Rottondi, C., Nag, A., Macaluso, I., Zibar, D., Ruffini, M., & Tornatore, M. (2018). An overview on application of machine learning techniques in optical networks. *IEEE Communications Surveys & Tutorials*, *21*(2), 1383-1408.
[92]. Nanthakumaran, P., & Tilakaratne, C. (2017). A comparison of accuracy of forecasting models: A study on selected foreign exchange rates. 2017 seventeenth international conference on advances in ICT for emerging regions (ICTer),
[93]. Naranjo, P. G. V., Pooranian, Z., Shojafar, M., Conti, M., & Buyya, R. (2019). FOCAN: A Fog-supported smart city network architecture for management of applications in the Internet of Everything environments. *Journal of parallel and distributed computing*, *132*, 274-283.
[94]. Nguyen, H., Kieu, L. M., Wen, T., & Cai, C. (2018). Deep learning methods in transportation domain: a review. *IET Intelligent Transport Systems*, *12*(9), 998-1004.
[95]. Nishat, J., & Mst Kaniz, F. (2022). A Review of the Impact of Covid-19 On Maternal and Child Health Service Utilization in Bangladesh. *American Journal of Scholarly Research and Innovation*, *1*(02), 223–269. https://doi.org/10.63125/vgv5s742
[96]. Ouyang, Y., Yang, C., Song, Y., Mi, X., & Guizani, M. (2022). A brief survey and implementation on refinement for intent-driven networking. *IEEE Network*, *35*(6), 75-83.
[97]. Perry, I., Li, L., Sweet, C., Su, S.-H., Cheng, F.-Y., Yang, S. J., & Okutan, A. (2018). Differentiating and predicting cyberattack behaviors using lstm. 2018 IEEE Conference on Dependable and Secure Computing (DSC),
[98]. Pham, D.-L., Ahn, H., Kim, K.-S., & Kim, K. P. (2021). Process-aware enterprise social network prediction and experiment using LSTM neural network models. *IEEE access*, *9*, 57922-57940.
[99]. Ramchandra, N. R., & Rajabhushanam, C. (2022). Machine learning algorithms performance evaluation in traffic flow prediction. *Materials Today: Proceedings*, *51*, 1046-1050.
[100]. Rathore, M. M., Ahmad, A., Paul, A., & Rho, S. (2016). Urban planning and building smart cities based on the internet of things using big data analytics. *Computer networks*, *101*, 63-80.
[101]. Rusek, K., Suárez-Varela, J., Almasan, P., Barlet-Ros, P., & Cabellos-Aparicio, A. (2020). RouteNet: Leveraging graph neural networks for network modeling and optimization in SDN. *IEEE Journal on Selected Areas in Communications*, *38*(10), 2260-2270.
[102]. Serpanos, D., & Wolf, M. (2018). Internet-of-Things (IoT) Systems. *Architectures, Algorithms, Methodologies*.
[103]. Sharma, P. K., Singh, S., Jeong, Y.-S., & Park, J. H. (2017). Distblocknet: A distributed blockchains-based secure sdn architecture for iot networks. *IEEE Communications Magazine*, *55*(9), 78-85.
[104]. Sharma, S. K., & Wang, X. (2017). Live data analytics with collaborative edge and cloud processing in wireless IoT networks. *IEEE access*, *5*, 4621-4635.
[105]. Shen, M., Ye, K., Liu, X., Zhu, L., Kang, J., Yu, S., Li, Q., & Xu, K. (2022). Machine learning-powered encrypted network traffic analysis: A comprehensive survey. *IEEE Communications Surveys & Tutorials*, *25*(1), 791-824.
[106]. Shi, J., Leau, Y.-B., Li, K., Park, Y.-J., & Yan, Z. (2020). Optimization and decomposition methods in network traffic prediction model: A review and discussion. *IEEE access*, *8*, 202858-202871.
[107]. Shu, Z., Wan, J., Lin, J., Wang, S., Li, D., Rho, S., & Yang, C. (2016). Traffic engineering in software-defined networking: Measurement and management. *IEEE access*, *4*, 3246-3256.
[108]. Sirignano, J., & Cont, R. (2019). Universal features of price formation in financial markets: perspectives from deep learning. *Quantitative Finance*, *19*(9), 1449-1459.
[109]. Sivanathan, A., Gharakheili, H. H., Loi, F., Radford, A., Wijenayake, C., Vishwanath, A., & Sivaraman, V. (2018). Classifying IoT devices in smart environments using network traffic characteristics. *IEEE Transactions on Mobile Computing*, *18*(8), 1745-1759.
[110]. Sone, S. P., Lehtomäki, J., Khan, Z., & Umebayashi, K. (2021). Forecasting wireless network traffic and channel utilization using real network/physical layer data. 2021 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit),
[111]. Sone, S. P., Lehtomäki, J. J., & Khan, Z. (2020). Wireless traffic usage forecasting using real enterprise network data: Analysis and methods. *IEEE Open Journal of the Communications Society*, *1*, 777-797.
[112]. Speiser, J. L., Miller, M. E., Tooze, J., & Ip, E. (2019). A comparison of random forest variable selection methods for classification prediction modeling. *Expert systems with applications*, *134*, 93-101.

[113]. Szostak, D., Włodarczyk, A., & Walkowiak, K. (2021). Machine learning classification and regression approaches for optical network traffic prediction. *Electronics*, *10*(13), 1578.
[114]. Tan, M., Yuan, S., Li, S., Su, Y., Li, H., & He, F. (2019). Ultra-short-term industrial power demand forecasting using LSTM based hybrid ensemble learning. *IEEE transactions on power systems*, *35*(4), 2937-2948.
[115]. Tang, B., Chen, Z., Hefferman, G., Pei, S., Wei, T., He, H., & Yang, Q. (2017). Incorporating intelligence in fog computing for big data analysis in smart cities. *IEEE transactions on industrial informatics*, *13*(5), 2140-2150.
[116]. Tang, Y., Cheng, N., Wu, W., Wang, M., Dai, Y., & Shen, X. (2019). Delay-minimization routing for heterogeneous VANETs with machine learning based mobility prediction. *IEEE Transactions on Vehicular Technology*, *68*(4), 3967-3979.
[117]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. *American Journal of Advanced Technology and Engineering Solutions*, *4*(04), 154-184. https://doi.org/10.63125/wmz8dc67
[118]. Torres, P., Marques, P., Marques, H., Dionísio, R., Alves, T., Pereira, L., & Ribeiro, J. (2017). Data analytics for forecasting cell congestion on LTE networks. 2017 Network Traffic Measurement and Analysis Conference (TMA),
[119]. Troia, S., Alvizu, R., Zhou, Y., Maier, G., & Pattavina, A. (2018). Deep learning-based traffic prediction for network optimization. 2018 20th International Conference on Transparent Optical Networks (ICTON),
[120]. Troia, S., Sapienza, F., Varé, L., & Maier, G. (2020). On deep reinforcement learning for traffic engineering in SD-WAN. *IEEE Journal on Selected Areas in Communications*, *39*(7), 2198-2212.
[121]. ur Rehman, M. H., Yaqoob, I., Salah, K., Imran, M., Jayaraman, P. P., & Perera, C. (2019). The role of big data analytics in industrial Internet of Things. *Future Generation Computer Systems*, *99*, 247-259.
[122]. Vinayakumar, R., Soman, K., & Poornachandran, P. (2017). Applying deep learning approaches for network traffic prediction. 2017 International conference on advances in computing, communications and informatics (ICACCI),
[123]. Walraven, E., Spaan, M. T., & Bakker, B. (2016). Traffic flow optimization: A reinforcement learning approach. *Engineering applications of artificial intelligence*, *52*, 203-212.
[124]. Wang, B., Zheng, Y., Lou, W., & Hou, Y. T. (2015). DDoS attack protection in the era of cloud computing and software-defined networking. *Computer networks*, *81*, 308-319.
[125]. Wang, K., Qi, X., & Liu, H. (2019). A comparison of day-ahead photovoltaic power forecasting models based on deep learning neural network. *Applied Energy*, *251*, 113315.
[126]. Wang, L., & Alexander, C. A. (2020). Big data analytics in medical engineering and healthcare: methods, advances and challenges. *Journal of medical engineering & technology*, *44*(6), 267-283.
[127]. Wang, Y., & Nakachi, T. (2020). Prediction of network traffic through light-weight machine learning. *IEEE Open Journal of the Communications Society*, *1*, 1919-1933.
[128]. Wu, J., Dong, M., Ota, K., Li, J., & Guan, Z. (2018). Big data analysis-based secure cluster management for optimized control plane in software-defined networks. *IEEE transactions on network and service management*, *15*(1), 27-38.
[129]. Wu, Y., Tan, H., Qin, L., Ran, B., & Jiang, Z. (2018). A hybrid deep learning based traffic flow prediction method and its understanding. *Transportation Research Part C: Emerging Technologies*, *90*, 166-180.
[130]. Xiao, Y., Zhang, Z., Chen, L., & Zheng, K. (2018). Modeling stress path dependency of cyclic plastic strain accumulation of unbound granular materials under moving wheel loads. *Materials & Design*, *137*, 9-21.
[131]. Yan, Q., & Yu, F. R. (2015). Distributed denial of service attacks in software-defined networking with cloud computing. *IEEE Communications Magazine*, *53*(4), 52-59.
[132]. Yan, Q., Yu, F. R., Gong, Q., & Li, J. (2015). Software-defined networking (SDN) and distributed denial of service (DDoS) attacks in cloud computing environments: A survey, some research issues, and challenges. *IEEE Communications Surveys & Tutorials*, *18*(1), 602-622.
[133]. Yang, H., Li, X., Qiang, W., Zhao, Y., Zhang, W., & Tang, C. (2021). A network traffic forecasting method based on SA optimized ARIMA–BP neural network. *Computer networks*, *193*, 108102.
[134]. Yin, X., Wu, G., Wei, J., Shen, Y., Qi, H., & Yin, B. (2021). Deep learning on traffic prediction: Methods, analysis, and future directions. *IEEE Transactions on Intelligent Transportation Systems*, *23*(6), 4927-4943.
[135]. Yu, H., Wu, Z., Wang, S., Wang, Y., & Ma, X. (2017). Spatiotemporal recurrent convolutional networks for traffic prediction in transportation networks. *Sensors*, *17*(7), 1501.
[136]. Yue, C., Wang, L., Wang, D., Duo, R., & Nie, X. (2021). An ensemble intrusion detection method for train ethernet consist network based on CNN and RNN. *IEEE access*, *9*, 59527-59539.
[137]. Zhang, F., Wu, T.-Y., Wang, Y., Xiong, R., Ding, G., Mei, P., & Liu, L. (2020). Application of quantum genetic optimization of LVQ neural network in smart city traffic network prediction. *IEEE access*, *8*, 104555-104564.
[138]. Zhang, H., Kang, C., & Xiao, Y. (2021). Research on network security situation awareness based on the LSTM-DT model. *Sensors*, *21*(14), 4788.
[139]. Zhang, J., Chen, F., Cui, Z., Guo, Y., & Zhu, Y. (2020). Deep learning architecture for short-term passenger flow forecasting in urban rail transit. *IEEE Transactions on Intelligent Transportation Systems*, *22*(11), 7004-7014.
[140]. Zhang, K., Zheng, L., Liu, Z., & Jia, N. (2020). A deep learning based multitask model for network-wide traffic speed prediction. *Neurocomputing*, *396*, 438-450.
[141]. Zhang, L., Yan, H., & Zhu, Q. (2020). An improved LSTM network intrusion detection method. 2020 IEEE 6th International conference on Computer and Communications (ICCC),
[142]. Zhang, Y., Chen, B., Pan, G., & Zhao, Y. (2019). A novel hybrid model based on VMD-WT and PCA-BP-RBF neural network for short-term wind speed forecasting. *Energy Conversion and Management*, *195*, 180-197.
[143]. Zhang, Y., Wang, S., Chen, B., Cao, J., & Huang, Z. (2019). TrafficGAN: Network-scale deep traffic prediction with generative adversarial nets. *IEEE Transactions on Intelligent Transportation Systems*, *22*(1), 219-230.

[144]. Zhao, Z., Chen, W., Wu, X., Chen, P. C., & Liu, J. (2017). LSTM network: a deep learning approach for short-term traffic forecast. *IET Intelligent Transport Systems*, *11*(2), 68-75.
[145]. Zheng, K., Yang, Z., Zhang, K., Chatzimisios, P., Yang, K., & Xiang, W. (2016). Big data-driven optimization for mobile networks toward 5G. *IEEE Network*, *30*(1), 44-51.
[146]. Zheng, X., & Leivadeas, A. (2021). Network assurance in intent-based networking data centers with machine learning techniques. 2021 17th International conference on network and service management (CNSM),
[147]. Zhou, K., Wang, W., Huang, L., & Liu, B. (2021). Comparative study on the time series forecasting of web traffic based on statistical model and Generative Adversarial model. *Knowledge-Based Systems*, *213*, 106467.
[148]. Zhu, L., Yu, F. R., Wang, Y., Ning, B., & Tang, T. (2018). Big data analytics in intelligent transportation systems: A survey. *IEEE Transactions on Intelligent Transportation Systems*, *20*(1), 383-398.