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AI-Driven Capacity Planning for 5G Optical Transport Networks under Saudi Vision 2030

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Abstract- As part of Vision 2030, Saudi Arabia is fast-tracking digital transformation, expanding 5G connectivity, cloud services, smart cities, industrial automation and data-intensive applications. These developments put pressure on optical transport networks as mobile fronthaul, midhaul, backhaul and data-center interconnection require scalable capacity, low latency and resilient routing. In this review, we focus on the role of artificial intelligence in the capacity planning of 5G optical transport networks through the integration of traffic forecasting, quality-of-transmission estimation, topology awareness, CAPEX optimization and executive governance. We conducted a structured narrative review of machine learning in optical networks, traffic-driven service provisioning, 5G fronthaul design and Saudi digital infrastructure, for the period 2020-2025. In this paper we propose a layered planning framework that ingests telemetry, inventory, service demand and external development signals and transforms them into staged capacity decisions. The review concludes that AI should not supplant engineering judgement, but enhance planning evidence, shorten reaction time, improve investment timing and support Vision 2030 readiness across metro, intercity, edge and critical infrastructure corridors.

Keywords: AI Capacity Planning, 5G Optical Transport, Saudi Vision 2030, Traffic Forecasting, CAPEX Optimization, Optical Networks, Telecom Operators.

I. INTRODUCTION

Saudi Arabia's telecom networks are becoming a strategic infrastructure layer to support economic diversification, digital government, cloud services, smart cities, industrial automation and artificial intelligence workloads. Connectivity is no longer a consumer communication service but a production platform for data centres, ports, airports, logistics corridors, energy facilities, entertainment zones, healthcare platforms and remote education under Vision 2030. Fifth generation mobile services further intensify this requirement as radio access densification, massive multiple-input multiple-output antennas and edge computing and low latency enterprise applications put strong pressures on the optical transport layer behind the radio network. Hence, optical transport networks must expand before congestion becomes visible to customers. Traditional planning methods are becoming more and more misaligned with traffic volatility and capital discipline in annual growth assumptions, manual spreadsheet dimensioning and conservative overprovisioning. Recent studies about intelligent optical networks show that machine learning could support forecasting, quality-of-transmission estimation, resource management and failure prediction in a way to improve planning accuracy and operational autonomy [1-3]. Demand manifests itself at multiple time scales, complicating capacity planning for 5G optical transport. Daytime spikes in traffic are driven by social media and residential streaming. Events, tourism and pilgrimage travel impact weekly and seasonal peaks. As factories, campuses, oil and gas facilities, hospitals and government platforms digitise their operations, industrial traffic changes. Cloud regions, artificial intelligence workloads or enterprise migration programmes can all go live, driving up demand for data centre interconnection. Mobile fronthaul, midhaul and backhaul also have different latency, synchronisation and bandwidth requirements, especially when centralised or virtualized radio access architectures are introduced [4,5]. But planners in Saudi Arabia must add geographic diversity to this complexity. The growth profiles, fibre availability, route risks and service priorities in Riyadh, Jeddah, Dammam, NEOM, industrial cities, religious cities, logistics hubs and far-flung locations are different. Such differences cannot be reflected by one national percentage growth factor. Capacity planning with AI-driven provides a structured response. Rather than asking if a link is full today, it estimates at what point each fibre span, wavelength system, router port, transponder shelf, amplifier chain or edge site will cross a risk threshold under a number of demand scenarios. It can integrate telemetry, trouble tickets, customer orders, mobile traffic counters, enterprise service records, population data, site expansion plans, cloud demand and macro-economic indicators. Forecasting models then assist in multi-period expansion decisions and optimization models evaluate the capital expenditure required to meet future capacity, latency and resilience requirements. This review discusses how such planning can help Saudi telecom operators to align their 5G optical transport expansion with Vision 2030. The intention is not to present a vendor specific design but to synthesise the technical and governance principles required for a repeatable planning framework.

II. AIM, OBJECTIVES AND CONTRIBUTION

This review aims to evaluate the role of artificial intelligence in enhancing the capacity planning of 5G optical transport networks in Saudi Arabia in line with the Vision 2030 objectives of digital infrastructure, industrial competitiveness, and service reliability. The first objective is to identify the drivers of capacity pressure in 5G optical transport. These include mobile broadband growth, enterprise private networks, cloud migration, edge computing, giga-project development, smart city services and critical infrastructure digitisation. The second objective is to survey AI techniques that can be applied to capacity forecasting, anomaly detection, traffic clustering, link utilisation prediction, demand localisation and investment prioritisation. The third objective is to link the forecasting outputs to optical planning decisions such as wavelength activation, coherent transceiver selection, fibre route expansion, packet-optical integration, protection design and CAPEX staging. The fourth objective is to propose a framework for Saudi Arabia-aligned operators that incorporates telemetry, planning databases, cost models, regulatory priorities, and executive dashboards. There are three contributions of the paper. First, it unifies recent literature on machine learning for optical networks, traffic-driven provisioning, 5G fronthaul design, cost-efficient transport and network automation in a single capacity-planning point of view [1-8]. Second, it maps those concepts to the Saudi context in which the connectivity investment has to be in support of the national digital transformation, high-speed mobile performance and a growing ICT economy [9-13]. Third, it proposes a pragmatic review framework that links the AI predictions to planning decisions that can be audited by engineering, finance, operations and strategy teams. The crux of the argument is that AI does not replace optical planning expertise, it adds to the evidence base, accelerates reaction times and allows for better timing of investments.

III. REVIEW METHODOLOGY

This paper adopts a structured narrative review approach appropriate for a multidisciplinary topic that spans optical engineering, artificial intelligence, telecom economics and national digital policy. The method comprises six stages: defining scope, identifying sources, screening, thematic coding, synthesis and framework development. The search was restricted to literature and institutional reports published between 2020 and 2025. Sources were included if they addressed at least one of the four themes: AI or machine learning in optical networks; 5G transport, fronthaul or backhaul planning; techno-economic or CAPEX-aware network expansion; and Saudi digital infrastructure under Vision 2030. The literature search covered Scopus, IEEE Xplore, Web of Science, and ScienceDirect. The search identified 148 records; 103 remained after duplicate removal and were screened by title and abstract. 61 full-text sources were assessed for eligibility, and 30 sources were included in the qualitative synthesis. Eligibility required direct relevance, publication within 2020–2025, sufficient methodological detail, and an identifiable scholarly or institutional source. The selection process is summarized in the PRISMA-style flow diagram below.

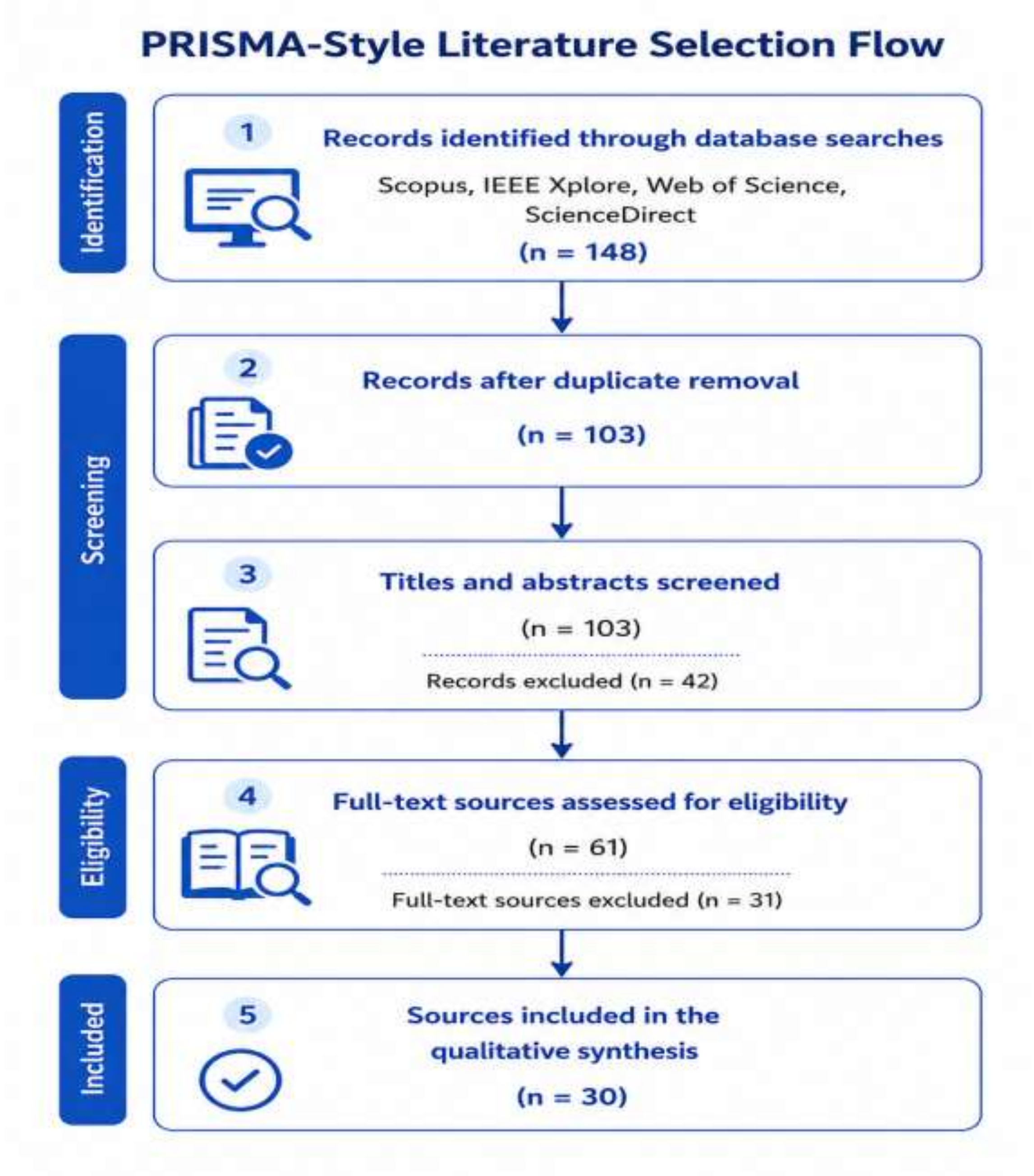

Figure 1. PRISMA-style flow of identification, screening, eligibility assessment, and inclusion.

The search terms were AI-driven optical network planning, machine learning optical networks, traffic prediction optical transport, 5G fronthaul planning, capacity forecasting telecom operators, packet optical transport, quality of transmission prediction, CAPEX optimization, Saudi digital infrastructure, Vision 2030 ICT and 5G Saudi Arabia. Priority was given to peer-reviewed articles on forecasting models, resource provisioning, quality-of-transmission estimation, elastic optical networks, passive optical fronthaul or cost-efficient transport. Official and industry sources were included if they provided evidence specific to Saudi on the growth of the digital economy, internet penetration, expansion of the ICT market, fibre coverage, 5G coverage, or operator transformation [9–13]. This mixed evidence base is appropriate, because capacity planning is not a pure academic optimization problem. It is implemented through real budgets, route permits, vendor road maps, service commitments and regulatory expectations.

Thematic coding was used for the synthesis. The studies were grouped into six categories: demand drivers, AI forecasting techniques, optical-layer planning, packet-optical integration, economic prioritisation, and Saudi deployment requirements. The categories were evaluated in terms of relevance to capacity planning, data needs, barriers to implementation and potential contribution to Vision 2030. The review does not present proprietary traffic data and does not present a new mathematical optimization model. Instead, it develops a conceptual and operational framework that can later be tested against operator data. This restriction is intentional: public evidence is enough to define the planning architecture, while exact investment values demand confidential network inventories, vendor pricing and traffic forecasts.

IV. SAUDI VISION 2030 CONTEXT FOR OPTICAL TRANSPORT EXPANSION

Saudi Arabia has established a robust digital transformation platform by investing heavily in communications infrastructure, e-government, cloud adoption and national technology programmes. According to official sources, the ICT and telecommunication markets are growing fast with very high internet penetration [9-11]. The Communications, Space and Technology Commission said that internet penetration was 99% in 2024 and Saudi Arabia was among the top G20 countries for mobile internet speeds [9]. MCIT reported the continuous growth of the digital economy and ICT market. Vision 2030 reporting emphasises digital infrastructure as the basis for economic transformation [10–12]. stc's public reporting also indicates continued investment in 5G, fibre, data centres, transport and network cloudification [13]. These trends indicate that optical transport networks need to scale continuously, not in fits and starts. Transport has specific needs under Vision 2030. Smart city districts and giga-projects need high-capacity access and aggregation networks prior to full population and enterprise occupancy. Deterministic connectivity is needed for automation, safety systems, logistics platforms and digital twins in industrial cities. Tourism and entertainment areas need seasonal flexibility. Cloud regions and data centres must be interconnected reliably, with predictable latency and protection.

Healthcare, government and financial services require resilient pathways, cybersecure operations and strong service availability. Studies on 5G-Advanced and future 6G also show larger radio bandwidth, denser sites and more demanding optical fronthaul requirements [5, 14].

Therefore, capacity planning should consider not only average traffic but also service criticality, event-driven peaks, edge node placement and failure resilience. Another issue specific to Saudi is the diversity of geography and environment. Desert heat, dust, long intercity routes, coastal humidity, urban construction and route concentration can affect performance and maintenance risk. While AI forecasting can estimate demand, route planning teams also need to take into account physical route constraints, availability of power, access to ducts, rights-of-way, spare fibre, and regional maintenance capacity. In Riyadh or Jeddah capacity expansion can focus on metro rings and data centre corridors. Remote regions can focus on resilient long-haul routes and aggregation efficiency. The AI planning becomes more useful if it can encode these differences, rather than assume that the same growth curve applies everywhere.

V. AI METHODS FOR CAPACITY FORECASTING

At its analytical core, AI-driven capacity planning is based on traffic forecasting. Forecasts can be produced at several granularities, e.g., cell site, aggregation ring, edge data centre, metro link, intercity route, wavelength, service class or customer segment. Traditional methods such as linear growth and moving averages are transparent but struggle with nonlinear peaks, sudden launches of services and spatial migration of demand. Machine learning algorithms like random forests, gradient boosting, support vector regression, recurrent neural networks, long short-term memory networks, temporal convolutional networks, and graph neural networks are able to learn more complicated patterns with enough data [1,6,7]. Traffic-driven provisioning, multi-step prediction and adaptive planning approaches have been investigated in optical network research to reduce over-provisioning while meeting quality-of-service requirements [3,6,7]. The choice of AI methods should be driven by the purpose of planning. Short-term forecasts are useful for operations like reconfiguration, congestion management and maintenance window planning. The medium-term forecasts support the activation of the transceiver, port upgrades, route balancing and budget allocation. Long-term forecasting helps with fibre route expansion, new metro rings, edge data centre location and vendor roadmap alignment. Useful features for Saudi operators can include historical utilisation, radio traffic counters, smart city occupancy milestones, enterprise order pipelines, customer experience indicators, population density, event calendars, cloud workload signals, IoT deployment zones and seasonality variables. A model trained solely on historical link utilisation might not capture external demand signals related to giga-project construction, tourism events or enterprise digitalisation. Interpretability is important. Significant CAPEX will not be approved by finance committees and network executives just because a black-box model predicts congestion. Planning models should therefore generate interpretable results: forecast confidence intervals, demand drivers, risk thresholds, impacted services, alternatives and expected utilisation after upgrade. Explainable AI approaches can point out if a forecast is being driven by mobile traffic, enterprise orders, cloud interconnection, recurring peaks or abnormal telemetry. This builds confidence and helps planners to differentiate structural growth from the short-term deviations. It also supports regulatory and internal audit requirements since investment decisions can be traced to evidence. Data quality is a perennial problem. Telecom data could be incomplete, delayed, inconsistent between vendors or reside in separate planning, operations and finance systems. Capacity planning needs a common inventory of fibres, ducts, spans, amplifiers, ROADMs, transponders, routers, switches, edge sites, radio sites and customer services. Without the right topology, you can't turn AI forecasts into actionable expansion decisions. A link may be uncongested at the aggregate level, but a particular service class, protection route or wavelength group is running out of capacity. So, AI planning must start with data governance before deploying models.

VI. FROM FORECASTING TO OPTICAL TRANSPORT PLANNING

Forecasts only work when they are turned into workable transport decisions. Lighting spare wavelengths, adding coherent transceivers, upgrading line systems, rebalancing traffic, increasing spectrum efficiency, deploying flex-grid capabilities, adding fibre pairs, redesigning protection paths or introducing higher-capacity packet-optical nodes are all ways in which the capacity of optical networks can be increased. Each action has a different cost, lead time, operational disruption, and risk. This requires that AI-driven planning map predicted demand to these choices. For example, if a 30% traffic increase is forecasted on a metro aggregation ring, this can be solved by lighting spare 400G wavelengths, if the optical power budget and spectrum allow it. A multiyear surge in a data centre corridor might require 800G coherent upgrades or new fibre routes. Staged aggregation upgrades may be favoured over immediate full route duplication, anticipating a rise in rural demand. At the heart of this translation is the quality of transmission. High-capacity coherent channels are distance and spectrum loading sensitive and affected by noise, fibre characteristics, amplifier performance, nonlinear impairments. To improve lightpath feasibility decisions and reduce conservative margins, machine learning for quality-of-transmission prediction is reviewed [2]. This is important for capacity planning, since any unnecessary margin consumes spectrum or adds more regeneration. AI-supported quality estimation can help planners decide if a new service could be routed over existing infrastructure or if regeneration is needed or a route should be upgraded. But you still need to know about the physical layer. ML outputs should be cross checked against engineering rules, field measurements and vendor specifications.
Packet-optical integration takes it to the next level. 5G transport often needs coordination between IP/MPLS, segment routing, synchronisation, Ethernet transport, WDM systems and sometimes passive optical technologies for fronthaul. C-RAN and virtualized RAN architectures can reduce the complexity of radio sites at the expense of increased requirements on

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fronthaul latency and capacity [4,5]. So, AI planning should consider the whole service path rather than only the optical link. A low-cost optical route may not be acceptable if it violates latency or resilience constraints. However, to engineer every route for the most demanding service is a waste of capital. Service-aware planning groups traffic by requirements and assigns transport resources.

VII. CAPEX OPTIMIZATION AND ECONOMIC GOVERNANCE

Planning of telecom capacity is as much an economic problem as a technical problem. Operators must avoid under-investment and creating congestion and customer dissatisfaction, and over-investment tying up capital in assets that are not used. Artificial intelligence can help optimise CAPEX by estimating when and how much demand will be needed, ranking which upgrades are candidates, comparing alternatives and finding shared investments that meet multiple future needs. The studies of techno-economic modelling of optical and fronthaul networks emphasise the significance of linking component costs, traffic scenarios, deployment constraints and energy consumption [4,8]. Vendor prices are proprietary, but normalised cost models can assist in comparing upgrade options on a consistent basis. A useful CAPEX framework would comprise direct equipment costs, installation, civil works, power, space, licenses, operations, spares, maintenance and service disruption risk. It should also include opportunity cost. Delaying an upgrade may save some capital this quarter but may cause a degradation of customer experience or constrain enterprise contract wins. Accelerating an upgrade might create a strategic advantage in an industrial zone, but it might reduce the short-term return on invested capital. AI is unable to tell the business where to go, but it can show the evidence of potential scenarios to executives.

It can show estimated cost per added Gbps, cost per protected site, avoided congestion risk, service revenue exposure, and demand uncertainty sensitivity. CAPEX governance for Saudi operators should align with national priorities. Investments in critical infrastructure, cloud corridors, industrial zones, airports, ports, hospitals and pilgrimage-related services may deserve higher resilience weighting than ordinary residential capacity. Vision 2030 also aims to build local capabilities and expand the digital sector [10–12]. Localisation indicators to be considered in planning decisions can include local integration, Saudi engineering skills, domestic operations capability and vendor-neutral interoperability. Table 1 shows the main review themes related to AI planning and operator decisions.

Table 1. Review synthesis of AI-driven capacity planning mechanisms for 5G optical transport.

Planning layer	Main function	Operator decision supported	Saudi relevance
Demand forecasting	Predicts growth by link, site, region and service class	When and where capacity will be exhausted	Supports smart cities, industrial zones and data centers
QoT and feasibility	Checks reach, impairment, spectrum and protection constraints	Whether demand can be routed on existing optical assets	Reduces conservative overbuild on long routes
CAPEX optimization	Compares staged upgrades, technology choices and timing	Which investment delivers the best cost-risk balance	Aligns capital with Vision 2030 corridors
Scenario governance	Tests high-growth, budget, resilience and event scenarios	How plans perform under uncertainty	Prepares for pilgrimage, giga-project and cloud demand
Continuous learning	Compares forecasts with post-upgrade utilization	How models and thresholds should be updated	Creates a national capability for smarter planning

VIII. PROPOSED FRAMEWORK

The suggested framework consists of five layers. The first layer is the data base. It consolidates telemetry, inventory, service records, radio growth, customer demand, outage history, fibre routes, site power and financial data. The second layer is prediction. It generates short-, medium- and long-term demand forecasts with uncertainty ranges at link, site, metro, intercity and service class levels. The third layer is engineering simulation. It evaluates the ability of the forecasted demand to be served over the existing routes, wavelengths, transponders, packet nodes and protection schemes under the constraints of latency, synchronisation and quality-of-transmission. Fourth layer is economic optimization. It looks at upgrade packages in terms of CAPEX, OPEX, energy, service impact, implementation lead time and strategic value. The fifth layer is learning and governance. It monitors forecast accuracy, tracks actual utilisation post upgrades, updates models and reports results to engineering and executive stakeholders. The architecture of this framework is illustrated in Figure 1. It starts with network and market signals, and ends with staged capacity roadmaps. The figure deliberately places planning governance in the centre because AI predictions, engineering simulations and CAPEX models need to be aligned. Without governance, planning teams can set up separate dashboards that don't inform aligned investment decisions. With governance the framework can define who owns data, who approves forecast thresholds, who validates engineering feasibility, who approves CAPEX and who reviews model performance.

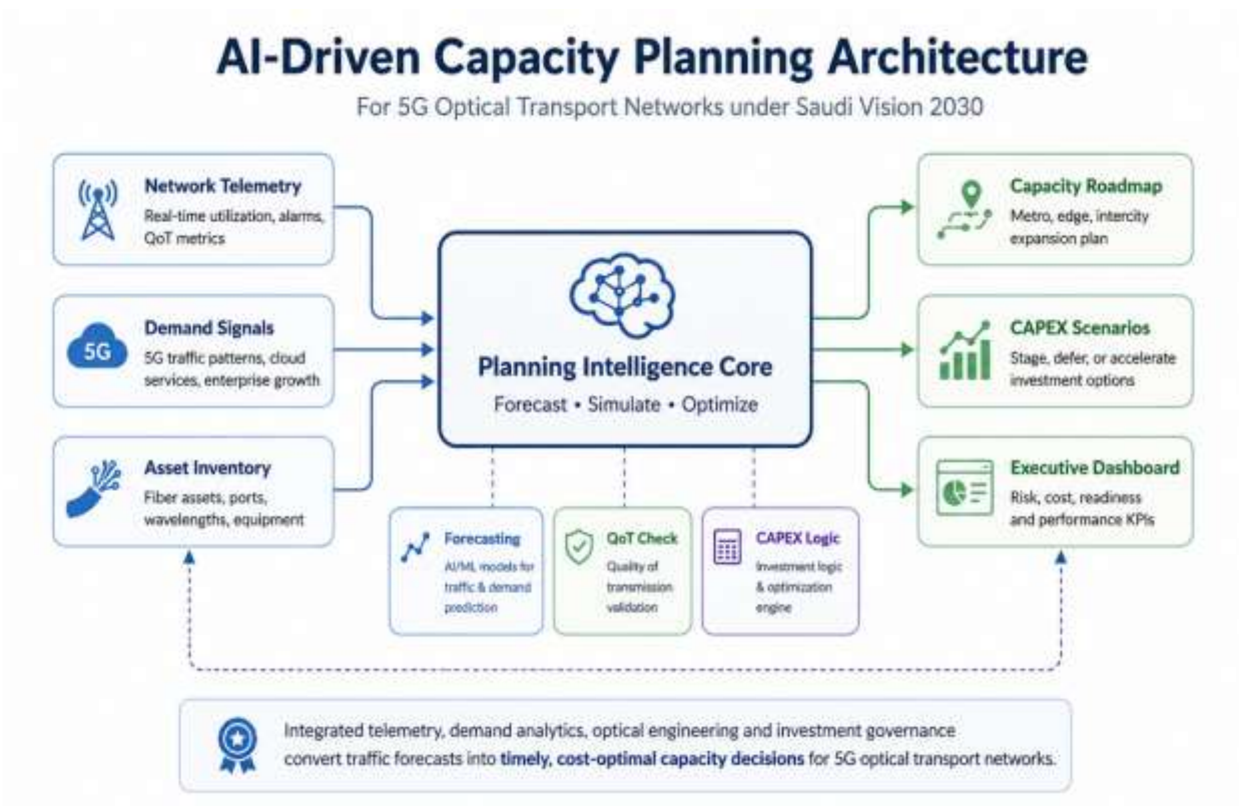

Figure 1. AI-driven capacity planning architecture linking network data, forecasting, engineering simulation and CAPEX governance.

The framework also needs to have maturity stages. Early maturity is focused on data cleanup, topology validation and manual forecast comparison. Intermediate maturity adds risk scoring based on dashboards and machine learning forecasts. Advanced maturity integrates forecasting with design tools, CAPEX models and auto-generation of scenarios. Autonomy makes recommendations in a closed-loop, but the final sign-off on major investments is still with engineering and finance. Saudi operators should not skip straight to autonomous planning. A phased approach builds trust and reduces risk during implementation.

IX. IMPLEMENTATION ROADMAP FOR SAUDI OPERATORS

Prioritise high-value planning areas. Metro aggregation around dense urban and enterprise zones is a practical first domain since traffic data are rich, and upgrade cycles are frequent, and business impact is visible. The second domain is data centre interconnection as cloud and AI workloads can produce concentrated growth. A third domain is critical infrastructure connectivity, where resilience and service continuity are strategic priorities. A fourth domain is long-haul route planning between major cities and giga-project areas. A phased roadmap is outlined in Table 2.

The first phase involves readiness assessment. Operators should audit inventory accuracy, fibre capacity, spectrum utilisation, transponder shelves, router ports, data quality and current forecasting practice. The second phase is pilot modelling. A small number of metro rings or corridors can be chosen to compare forecasts against historical growth. The third phase is engineering integration, connecting forecasts to the optical planning tools, quality-of-transmission checks and protection constraints. The fourth stage is CAPEX governance where alternatives are compared on normalised cost and strategic value. The fifth phase is continuous learning where the forecast errors and post upgrade utilisation are fed back into the model. The organisational change is as important as the technical model. Assumptions need to be aligned among planning, operations, finance, radio engineering, enterprise sales, cloud teams and procurement. A sales team might know about an upcoming industrial customer long before traffic hits the network. A radio team might know where 5G densification is planned. A cloud team might know that a data centre corridor will need additional capacity. These signals are integrated and AI planning gets stronger. In contrast, a model based only on network counters may have been accurate in the past, but may be fragile in predicting strategic growth.

Table 2. Saudi implementation roadmap for AI-driven 5G optical transport capacity planning.

Phase	Focus	Priority actions	Expected planning value
1. Readiness	Data and inventory foundation	Validate topology, assets, utilization, service classes and planning ownership	Trustworthy baseline for forecasting and engineering simulation
2. Pilot modeling	High-value metro and data center corridors	Train models, compare against history and define risk thresholds	Early evidence of forecast usefulness and limitations
3. Engineering integration	Optical feasibility and packet-optical design	Connect forecasts to QoT checks, protection paths and capacity alternatives	Feasible upgrade options instead of isolated predictions
4. CAPEX governance	Investment prioritization and scenario analysis	Rank upgrades by cost, lead time, service criticality, revenue risk and resilience	Better timing of wavelength, port, route and fiber investments
5. Continuous learning	Operational feedback and model governance	Review forecast error, actual utilization, outages and customer impact	Sustained improvement and audit-ready planning culture

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Figure 2. Continuous AI planning cycle for forecasting, simulation, optimization, deployment and learning.

X. DISCUSSION

Saudi operators can use AI-driven capacity planning to move from reactive expansion to proactive infrastructure management. The biggest benefit is not just forecast accuracy it is the ability to link demand, engineering feasibility and investment timing in one decision process. This is especially true when considering Vision 2030 where digital infrastructure needs to be put in place for high growth sectors before bottlenecks occur that affect the quality of service. Late capacity expansion in telecom networks can be expensive as equipment procurement, route construction, permits, civil works and integration often demand long lead time. Artificial intelligence can help identify risks sooner and assist in phased investment. But we need to be careful not to overpromise AI-driven planning. Forecasts can go wrong where demand patterns change due to new services, regulatory changes, major events, economic shifts or unexpected customer behaviour. Planning should therefore be based on scenarios, but not on a single deterministic forecast. We can think of a base scenario as growth as expected, a high-growth scenario as cloud/giga-project/event acceleration, a resilience scenario as failure or route constraint, and a constrained-budget scenario as minimum viable upgrades. Scenario planning prevents operators from suffering from false precision.

A second problem is model bias. When history has favoured investment in densely populated urban regions, models might predict higher growth there and underestimate latent demand in underserved regions. The national development and digital inclusion objectives are part of the Vision 2030, so the planning cannot be based on historical traffic only. Clear inputs should include strategic priorities and policy objectives. Capacity may be required in remote areas, industrial corridors and new urban development's prior to traffic history justifying the investment. In these cases, AI should assist in planning by integrating external indicators, not just extrapolating old utilisation.

A third problem is the cyber and operational resilience.

AI planning platforms will hold sensitive information about network topology, spare capacity, customer services and strategic investments. Consequently, to provide protection, identity management, access control, encryption, logging and model governance are required. Corrupted topology or traffic data may lead to wrong upgrade recommendations and thus data integrity is crucial. Human supervision is also needed for resilience. Planners must be able to distinguish robust recommendations from those that depend on uncertain inputs. Implementation should also take into account procurement cycles and vendor roadmaps. Shelves, line cards, pluggables, amplifiers, routers, software licenses, synchronisation equipment, test tools and professional services provide optical transport capacity. And those elements don't all come in the same time frame. The price of them changes as the technology matures. Thus, a forecasting model finding future demand has to be linked with supply-chain planning. If 800G or 1.2T coherent optics are likely to bring down the cost per bit in a certain time frame, then planners may opt for an interim 400G activation instead of a big immediate rebuild. In contrast, early route preparation and space reservation could be cheaper than emergency civil works later if a strategic corridor is to be a backbone for cloud or giga-projects. Artificial intelligence can support this type of timing logic by comparing demand risk, lead time and technology readiness. Another practical concern is the migration of services. Upgrading capacity normally consists of moving services from old to new paths, reconfiguring protection, changing optical channels and coordinating maintenance windows. These activities create operational risk if the final design is better. So disruption indicators should be included in AI-driven planning. If there is an upgrade option available at a slightly higher equipment cost that prevents repeated service migrations or reduces the night-work windows, it may be better. And for critical customers, planned disruption can be as important as capacity price. It links technical planning with customer experience management.

The same framework can be used to support enterprise products. Operators that can forecast capacity availability by location can provide improved committed delivery dates for private 5G, cloud connectivity, internet exchange, managed security and data centre services. Planning information is a commercial asset. Sales teams see where capacity is available, where it is constrained and where a customer commitment would trigger a justified expansion. This results in improved alignment of network investment to revenue generation.

XI. PERFORMANCE METRICS AND VALIDATION LOGIC

Validation should connect forecast quality to planning outcomes. Operators should report MAE, RMSE and MAPE by horizon, alongside threshold-crossing accuracy, forecast bias, capacity headroom, cost per added Gbps, avoided emergency upgrades and post-investment utilization. Resilience, energy and governance weights should not be restated as separate arguments; they should enter the validation scorecard as explicit constraints and decision weights already defined in Sections 7 and 10. A model is useful only when its recommendations remain feasible under latency, protection, energy, budget and audit requirements [15–30].

XII. CONCLUSION

Using AI for the capacity planning of 5G optical transport networks in Saudi Arabia is a sound strategy. The demand for scalable, reliable and cost-effective optical infrastructure is being driven by the Kingdom's digital economy, high internet penetration, 5G development, smart city ambitions, cloud growth and industrial transformation. Recently, the literature demonstrates that machine learning can be used to support traffic forecasting, quality-of-transmission prediction, failure prediction and traffic-driven provisioning in optical networks. These capabilities along with engineering simulation and CAPEX governance give operators the ability to build more adaptive capacity roadmaps than traditional planning cycles. The review closes with a layered approach: establish robust data foundations, implement interpretable forecasting, validate optical feasibility, compare economic scenarios, and institutionalise ongoing learning. For Saudi operators, the framework should focus on critical corridors, industrial cities, data centre interconnections, giga-project regions and dense urban aggregation networks. AI should be considered as an enhancement of planning capability, not as a replacement for engineering judgement. Future work should include implementation of the proposed framework using Saudi traffic traces, vendor cost data, route inventories and field measurements, and quantify the reduction in overprovisioning, congestion risk and upgrade lead time.

Study-Level Comparison of Included Evidence

Table 3. Study-level comparison of representative evidence included in the review.

Author / year	Method	Dataset / evidence	Key result	Limitation
Gu et al. (2020)	Comprehensive survey	Optical-network ML literature	ML supports forecasting, QoT and automation	Heterogeneous datasets
Fayad et al. (2022)	ILP techno-economic model	TWDM-PON fronthaul scenarios	Delay-constrained planning lowers total cost	Model assumptions require operator calibration
Du et al. (2022)	Supervised prediction	Operational performance-monitoring records	Early warning of loss-of-signal risk	Rare-event class imbalance
Lykakis et al. (2025)	Systematic survey	5G traffic-prediction studies	Deep temporal models improve nonlinear forecasts	Limited cross-operator validation
Iovanna et al. (2025)	Architecture evaluation	Future C-RAN transport scenarios	Flexible transport supports staged scaling	Vendor and deployment dependencies

Quantitative Findings Reported in the Literature

Table 4. Quantitative findings and measurable implications reported or operationalized from the cited evidence.

Study	Quantitative measure	Reported value / range	Planning implication
Fayad et al. (2022)	Publication design space	TWDM-PON split and delay scenarios	Use delay constraints when comparing lowest-cost designs
CST (2025)	Internet penetration	99% (2024)	Plan for sustained high baseline demand
3GPP Rel. 17	Architecture baseline	5G SA transport requirements	Dimension latency, synchronization and resilience jointly
Lykakis et al. (2025)	Forecast horizon	Short-, medium- and long-term models	Match model horizon to upgrade lead time

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