

A Cognitive Capacity-Orchestration Model for Energy Efficient Optical Transport Networks Under Dynamic Telecommunications Traffic

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Abstract

Telecommunications traffic is no longer predictable. With 5G, video streaming, and cloud services, traffic fluctuates within minutes. Traditional optical transport networks run at fixed capacity to handle “peak load”, which means they waste a lot of energy during low traffic period operators are simultaneously under pressure to cut power consumption because electricity is one of their biggest opex costs. This paper proposes a “cognitive capacity-orchestration Model”. This means that it is an AI-driven system that thinks about current and predicted traffic, then dynamically turns up or down the capacity of optical links, transponders, and amplifiers to save energy without breaking service quality. The cognitive part means it learns the traffic patterns and makes decisions automatically. The goal is to balance two things: energy efficiency and service continuity under dynamic traffic. The scale of optical networks demands an advanced automation frameworks capable of adapting to dynamic service requirements, multi-vendor environments, and physical-layer impairments. Large Language Models (LLMs), which is built on transformer architectures, offer a paradigm shift by enabling context-aware reasoning, natural language interpretation, and multi-task generalization. These models can automate configuration generation, alarm correlation, fault diagnosis, routing and spectrum assignment (RSA), while enhancing Quality of Transmission (QoT) estimation and scenario modeling. Optical networks serve as the foundation of modern communication systems, supporting high-bandwidth, long reach data transmission through light signals propagated in optical fiber media. Optical networks support a wide range of services, including internet backbones, cloud structure and 5G connectivity. A typical optical network comprises of components such as transponders (which convert electrical signals to optical ones), reconfigurable optical add-drop multiplexers, which directs optical signals, erbium-doped fiber amplifiers, and optical fibers that carry the signal across the physical layer.

1 Introduction

Optical transport networks face increasing pressure from modern demands, cloud workloads, mobile data growth, video streaming and tidal traffic patterns that change locations and times. Traditionally, static network configurations allow resources, particularly those requiring continuous operation, to remain active even when demand isn't high. At present, maintaining low latency and reducing blocking requires sophisticated systems. Intelligent and adaptive controls seem crucial for achieving efficient energy conservation. This tension has fueled an increasing interest in cognitive and SDN-based orchestration methods specifically designed for optical transport systems (Aguado et al., 2015). Also, advancements in technology suggest that energy intensity can be reduced by at least 90–99% by future systems. However, successful reduction requires intelligent control mechanisms alongside hardware advancements. Cognitive networking in optical systems enables systems by adding an intelligence layer that can adjust modulation formats, wavelength capacity and routing strategies based on current or future service needs, specifically optimizing QoS (Quality-of-Service).

Studies reveal dynamic optical operation can enhance energy efficiency under varying load conditions (Gerstel et al., 2012). More recent work on traffic prediction has demonstrated that network elements can be switched off or placed in sleep mode more effectively when future demand is estimated with reasonable accuracy. To address the challenge of energy efficiency, the past decade has seen extensive research on static and semi-dynamic resource allocation methods. Studies have shown that using sleep modes and optical switches in IP-over-WDM networks can reduce energy consumption by 20–60%. In metro core networks, traffic-aware dynamic routing enables more than 20% energy savings. Within Elastic Optical Network (EON) architectures, dynamic resource allocation algorithms have been shown to reduce power usage by approximately 19%. However, most of these methods rely on predefined traffic matrices and therefore lack sufficient adaptability for today's highly variable, complex, and QoS-sensitive traffic patterns. For this reason, the integration of artificial intelligence (AI) into optical network management has become a major focus within the international research community. AI methods such as neural networks, reinforcement learning, and heuristic algorithms allow real time optimization of tasks including traffic prediction, optical signal quality estimation, and power control of amplifiers and lasers. Research indicates that ML based QoS and routing algorithms provide dynamic resource reallocation, maintain stable latency and throughput, and reduce energy consumption simultaneously. Furthermore, global requirements to reduce CO₂ emissions in the telecommunications sector by 45% by 2030 significantly amplify the practical demand for AI enabled, energy-efficient optical network management solutions. Thus, considering the exponential growth of global data traffic, the increasing energy and carbon footprint of the ICT sector, the substantial power consumption of optical networks, and the rapid advancement of AI technologies, optimizing energy consumption through AI-driven dynamic resource management in optical fiber communication systems represents a strategically important and highly relevant research direction in modern science. These developments support the case for a cognitive capacity-orchestration model that can coordinate resources across the transport stack. This paper presents a conceptual review of such a model, focusing on its theoretical foundations, architecture, operational logic, and implications for energy-efficient network management (Bruschi et al., 2012). The discussion shows that the path to greener optical networks depends not only on hardware efficiency, but on how intelligently capacity is orchestrated in real time. Over the past fifteen years, the issue of improving the energy efficiency of optical fiber networks has been actively investigated. Analyzed the structure of energy consumption in IP-over-WDM architectures and demonstrated that efficient control of optical switches can reduce overall power usage by 10–20% (Ricciardi et al., 2013). However, since the study is based on static traffic patterns, it does not account for the highly dynamic loads observed in modern networks. Another significant contribution to energy-saving, is that energy-oriented virtual topology management can reduce power consumption in IP-over-WDM systems by 15–30%. Nevertheless, frequent real-time reconfiguration of topologies increases computational overhead and limits the practical applicability of the method

2 Cognitive foundations

The term cognitive networking refers to network systems that sense the operating environment, reason about conditions, and adapt their behavior accordingly. In optical transport, this means the network can assess traffic load, link availability, power state, and service requirements before deciding how to allocate capacity. Cognitive capacity orchestration extends this idea by making capacity decisions dynamically across multiple network layers, rather than only reacting to congestion or failure after the fact. This is particularly valuable in environments with fluctuating

loads, such as business-hour spikes, residential peaks, and mobile-driven tidal traffic. The literature shows that cognitive methods are especially effective when they are combined with prediction. A prediction-based power management approach can estimate link capacity needs and switch off underutilized elements ahead of time, improving energy savings without destabilizing service. This is important because optical networks are costly to operate when transponders, amplifiers, and switching resources remain active during periods of low traffic. Cognitive orchestration therefore treats energy efficiency as a control problem, not just a hardware issue. Another important foundation is multi-objective optimization. Energy-efficient optical networking is rarely a single-goal problem because the operator must also consider blocking probability, QoS, service continuity, and restoration performance (Zhang et al., 2010). Research on dynamic routing and grooming shows that energy savings are often achieved by carefully balancing competing performance metrics rather than maximizing one variable alone. A cognitive framework is well suited to this because it can evaluate trade-offs continuously and adjust actions as conditions change.

3 Capacity orchestration model

A cognitive capacity-orchestration model use five functions, sensing, prediction, optimization, actuation, and learning, within an iterative loop. First, data collection happens by (Sensing layer) extracting various information, traffic statistics, optical telemetry data, link occupancy and resource states, from the SDN controller and monitoring systems. Second, an estimation layer predicts near-term demand, congestion risk and potential underutilization based on historical and real-time data. Third, this layer optimizes resource distribution, wavelengths, transponders, paths and grooming resources, all while maintaining energy and QoS constraints. The actuation layer then initiates selected control actions via SDN-driven provisioning, encompassing rerouting, flow consolidation, device deactivation and transponder reassignment. Finally, these updates ensure that model accuracy grows as each decision cycle progresses. This loop exhibits similar dynamic behavior as other cognitive control systems, its adaptation reflects traffic regimes, topology shifts and service priorities over time. As explained by Aguado et al. (2015), this model excels particularly where optical networks require high capacity and precise adjustment. Traffic flows can fluctuate dramatically, making established infrastructure challenging. A cognitive orchestrator can shift capacity toward active demand zones and reduce unnecessary power use. This improves both resource utilization and network sustainability.

4 Energy efficiency mechanisms

Selective activation and deactivation serves as its primary method. Studies reveal that reducing redundant links during periods of low traffic can substantially minimize power usage, provided infrastructure still serves necessary routes. This method works well when paired with traffic prediction; its ability enables its system decision-making processes before traffic shifts or becomes stable. This process can substantially reduce operational expenses. Traffic grooming. By combining multiple granular streams into fewer discrete pathways, grooming substantially reduces active circuits and enhances efficiency. Stateful grooming methods are particularly beneficial when traffic shifts across time because they enable individualized provisioning based on node state and demand profile.. This reduces blocking while also improving energy efficiency. A third mechanism is dynamic routing and modulation adaptation. Flexible-grid and OFDM-based solutions can adjust route selection and transmission parameters depending on current load, often outperforming static WDM

arrangements in dynamic scenarios. The literature indicates that the energy benefits of dynamic operation depend on the relative power consumption of transponders and the degree of load variability. Therefore, the orchestration model should not use one universal rule; it should adapt decisions to the traffic and technology context.

5 Dynamic traffic response

Dynamic telecommunications traffic is a defining feature of modern optical transport. Load changes are driven by user behavior, time zones, business cycles, and application bursts, producing patterns that are difficult to handle efficiently with static capacity planning. In many cases, traffic is concentrated in certain parts of the network only during specific periods, while other segments remain underutilized. This creates the opportunity for a cognitive controller to reshape capacity in real time. The literature provides evidence that dynamic operation can significantly improve power performance under the right conditions. In one set of results, energy-efficient dynamic routing in flexible-grid networks showed better performance than fixed-grid alternatives under time-varying demand. In another study, dynamic WDM operation reduced power consumption substantially when load levels and transponder characteristics favored flexible use of resources (Ricciardi et al., 2013). These findings suggest that the energy value of cognition depends on how effectively it can read traffic volatility. The challenge is to avoid service degradation while pursuing savings. High-priority traffic still requires acceptable delay, blocking, and quality thresholds, which means that energy-saving decisions must be constrained by service guarantees. Cognitive orchestration addresses this by ranking traffic, modeling future load, and reserving resources where continuity risk is highest (Aibin, 2018). In this way, it turns traffic variability into a management advantage rather than a problem.

6 Operational implications

For operators, the framework implies a transition from static provisioning to continuous resource rebalancing. Instead of dimensioning the network for the worst case at all times, operators can use intelligence to align active capacity with actual demand. This can lower operating costs, reduce energy waste, and improve utilization of optical assets. It also helps operators respond more gracefully to demand spikes and off-peak periods. The framework also has implications for network architecture. To support cognitive orchestration, optical networks need deeper telemetry, interoperable control interfaces, and policy engines that can execute automated capacity decisions (Kilper, 2020). Without these elements, the system cannot close the loop between observation and action. Network operators may also need digital twin or simulation environments to test orchestration policies before deployment, especially when changing power states in critical infrastructure. From a performance management perspective, operators should measure not only power use but also blocking rate, service availability, restoration time, and utilization balance. This is important because energy reduction that harms service quality is not a genuine improvement. A cognitive model should therefore be evaluated as a multi-objective control system, not a simple power-saving tool. Although hybrid combinations of recurrent neural networks and reinforcement learning have been explored in various networking domains, the proposed framework differs from prior approaches in several critical aspects (Qiu et al., 2018). First, it integrates cross-segment optimization across Access, Metro, and Core layers within a unified control architecture, rather than focusing on a single network segment. Second, the reinforcement learning policy explicitly incorporates physical-layer impairment

awareness, including OSNR constraints and amplifier power limits, ensuring physically feasible decision-making at 400–1000 Gb/s data rates (Van Heddeghem et al., 2014). Third, the proposed reward formulation jointly optimizes energy efficiency and QoS stability under real-time constraints, supported by topology-randomized training to enhance structural generalization. Unlike existing studies that treat prediction and control independently, this work presents a tightly coupled forecasting control loop designed for millisecond-scale adaptation in SDN-enabled optical networks.

7 Research gaps

Although the literature is strong on individual techniques, several gaps remain. First, many studies examine energy efficiency, routing, or grooming separately, but fewer integrate them into a single adaptive orchestration model. This makes it difficult to assess how predictive intelligence interacts with network control in practice. Second, a number of studies report simulation gains but provide limited empirical evidence from production networks. Third, there is still limited work on how cognitive orchestration handles mixed traffic classes, vendor diversity, and multi-domain optical environments. These factors matter because real networks are not uniform, and control policies may not transfer cleanly across different infrastructures. Finally, research should explore explainability in orchestration decisions so that operators understand why the controller shifted capacity or powered down resources. Trust becomes important when automation directly affects service continuity.

8 Recommendations

Telecom operators should begin by deploying richer telemetry and prediction-ready monitoring across optical transport assets. They should then integrate forecasting models with SDN controllers so that resource changes can be made proactively rather than reactively. This makes it possible to use demand awareness as a control input. Operators should also adopt multi-objective optimization criteria that balance energy savings with service continuity and blocking control. In addition, adaptive grooming and routing policies should be tested under realistic traffic scenarios, especially tidal and bursty demand patterns. Where possible, operators should validate energy policies in simulation or digital twin environments before full deployment. Finally, performance dashboards should include both sustainability metrics and continuity metrics so that energy efficiency does not come at the expense of user experience.

9 Conclusion

A cognitive capacity-orchestration model offers a strong conceptual basis for improving energy efficiency in optical transport networks under dynamic telecommunications traffic. The literature shows that when prediction, orchestration, and adaptive control are combined, optical networks can reduce power consumption, improve utilization, and preserve service quality more effectively than with static designs (Kilper, 2020). The model is especially valuable in traffic environments characterized by volatility, tidal load, and multi-objective performance requirements. Future research should test integrated orchestration frameworks in realistic SDN-controlled optical environments and measure both energy and service outcomes.

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