

Machine Learning-Enabled Performance Optimization of Wavelength-Switched Networks

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Abstract

Wavelength-switched optical networks have long offered deterministic capacity, low latency, and high spectral efficiency, but their static provisioning models struggle with the dynamic traffic patterns of cloud, data center, and edge infrastructures. Machine learning introduces a promising control and optimization layer that can infer traffic behavior, predict quality of transmission, allocate wavelengths, and reconfigure optical paths with limited human intervention. This paper examines machine learning enabled performance optimization of wavelength-switched networks from a system-level perspective. It argues that optimization is not merely a computational problem but a socio-technical challenge involving architecture, operations, governance, sustainability, robustness, and fairness. The discussion first reviews the architectural foundations of wavelength switching, including reconfigurable optical add-drop multiplexers, elastic spectrum assignment, and intra-data center interconnects. It then analyzes how supervised learning, reinforcement learning, and probabilistic inference can improve routing, spectrum allocation, failure recovery, and energy management. Particular attention is given to structural trade-offs among latency, blocking probability, spectral efficiency, capital expenditure, and operational complexity. The paper also considers deployment constraints, telemetry requirements, model lifecycle management, and cross-domain lessons from software-defined networking and AI safety. It concludes that machine learning can enhance wavelength-switched network performance only when embedded within accountable governance frameworks, robust monitoring systems, and sustainability-aware planning. The central contribution is a critical synthesis that connects algorithmic optimization to infrastructure policy, fairness, and long-term resilience.

Keywords

machine learning; wavelength-switched networks; optical network optimization; data center interconnects; resilience; sustainability; governance.

1. Introduction

Wavelength-switched networks occupy a distinctive position in modern communication infrastructure because they combine the capacity of optical fiber with the predictability of circuit-oriented transport. Instead of routing every packet through electronic decisions at each hop, wavelength-switched architectures assign end-to-end or path-based optical channels that can remain stable for long periods [1]. This design reduces electronic processing, lowers latency, and simplifies traffic engineering for high-volume flows. However, the same design also creates rigidity. Once wavelengths are provisioned, they may be underused, stranded, or poorly matched to bursty traffic. The growth of cloud services, artificial intelligence training clusters, and distributed data centers has intensified this mismatch, because demand fluctuates across time, geography, and service class [2]. Machine learning has therefore emerged as a

practical means of making wavelength-switched networks more adaptive without abandoning their deterministic advantages.

The case for machine learning rests on the increasing availability of telemetry from optical transceivers, amplifiers, switches, and control planes. Modern networks generate large volumes of performance data, including optical power levels, bit error rates, latency, and alarm histories [8]. These data can support models that predict failures, estimate quality of transmission, and recommend reconfiguration actions. Early work on artificial intelligence in optical networks emphasized the potential of data-driven methods for fault management, performance monitoring, and resource assignment [8]. Subsequent surveys have broadened this agenda to include supervised learning, unsupervised clustering, reinforcement learning, and deep learning for optical network automation [9]. The appeal is clear: if a model can anticipate congestion or degradation before it affects service, operators can reroute wavelengths, adjust modulation formats, or reserve capacity with less disruption.

Yet optimization in wavelength-switched networks cannot be reduced to model accuracy. A high-performing algorithm may still fail if it ignores operational constraints, regulatory obligations, or the social distribution of network benefits. Machine learning models depend on data that may be incomplete, biased, or delayed, and their recommendations may be opaque to engineers responsible for critical infrastructure [16]. They also introduce new forms of technical debt when models, pipelines, and feature stores are not maintained with the same discipline as hardware [17]. In addition, the environmental cost of training and operating machine learning systems can offset some of the energy savings achieved through better optical routing [14]. For these reasons, this paper treats machine learning as an embedded control layer within a broader socio-technical system, not as a standalone solution.

This paper develops three main arguments. First, wavelength-switched networks benefit most from machine learning when models are integrated into closed-loop control architectures that combine optical domain knowledge with real-time telemetry. Second, performance optimization must be evaluated across multiple dimensions, including latency, spectral efficiency, resilience, fairness, and sustainability, rather than through a single efficiency metric. Third, the deployment of learning-based optimization requires governance mechanisms that address accountability, transparency, and long-term infrastructure policy. The discussion proceeds from architectural foundations to algorithmic opportunities, then to trade-offs, deployment challenges, ethical concerns, and forward-looking policy implications.

2. Architectural Foundations of Wavelength-Switched Networks

Wavelength-switched networks are built around the idea that a communication path can be assigned a dedicated wavelength or spectral slot across a sequence of optical nodes. Reconfigurable optical add-drop multiplexers and wavelength-selective switches allow operators to route wavelengths without converting them to electronics at every intermediate point [1]. This architecture supports high-capacity, low-power transport for long-lived flows, especially in backbone networks and data center interconnects. The introduction of elastic optical networking further improved flexibility by dividing the spectrum into finer granular units, enabling the network to allocate just enough spectrum for each demand rather than forcing all channels into a fixed grid [3]. Elastic approaches also permit distance-adaptive modulation, where shorter paths use higher-order modulation and longer paths use more robust formats [4].

Despite these advances, wavelength-switched architectures remain constrained by physical-layer effects and operational complexity. Optical signals degrade through attenuation, dispersion, nonlinear interference, and amplifier noise. The quality of transmission for an unestablished lightpath is difficult to predict precisely because it depends on the accumulated state of fibers, amplifiers, and switching elements [10]. In addition, wavelength continuity and spectrum contiguity constraints mean that a path may be blocked even when capacity exists in fragmented form [12]. These constraints create a combinatorial optimization problem that classical heuristics often solve adequately for static traffic but less effectively for dynamic or unpredictable demand. Machine learning can help by learning patterns in traffic and physical-layer behavior, but it cannot eliminate the underlying physical and architectural limits.

Intra-data center networks illustrate both the promise and the difficulty of wavelength switching. Data centers host thousands of servers that exchange bursty east-west traffic, and electrical packet switching has struggled to scale in bandwidth and energy efficiency [5]. Hybrid electrical and optical architectures such as Helios demonstrated how optical circuit switching can complement electrical switching for large flows [6]. More recent work has explored wavelength-switched, clock-synchronized interconnects enabled by hollow-core fiber to reduce latency and improve synchronization for time-sensitive workloads [7]. Such designs are attractive for machine learning clusters, storage replication, and distributed databases, where tail latency matters as much as average throughput. However, they require precise time synchronization, fast switch reconfiguration, and careful arbitration among tenants, all of which create new control-plane challenges.

The control plane of a wavelength-switched network is therefore as important as the data plane. Software-defined networking has been applied to transport networks to separate policy, path computation, and device configuration, enabling more programmable operations [11]. A centralized or logically centralized controller can collect telemetry, compute routes, and push wavelength assignments to optical nodes. Yet centralization introduces scalability and resilience risks, especially when the controller becomes a single point of failure. Distributed or hierarchical control architectures may be more robust, but they complicate coordination and consistency. Machine learning models can operate at either layer, but their placement affects latency, data availability, and trust. A model that runs near the optical devices can react quickly but may have limited context, while a cloud-hosted model can use more data but may introduce delay and dependency on external infrastructure [22].

3. Machine Learning as a Control and Optimization Layer

Machine learning can contribute to wavelength-switched networks in several functional areas, including traffic forecasting, quality-of-transmission prediction, routing and spectrum assignment, failure detection, and energy-aware reconfiguration. Supervised learning is well suited to prediction tasks where historical data include labels such as successful lightpath establishment or measured bit error rate. For example, models can estimate whether a proposed lightpath will meet a required quality threshold, reducing the need for conservative margins that waste spectrum [10]. Unsupervised learning can cluster traffic patterns, detect anomalies, or identify groups of wavelengths with similar degradation behavior. Reinforcement learning is attractive for sequential decision problems such as dynamic routing, where an agent learns policies by interacting with a simulated or real network environment [9]. These methods can complement, rather than replace, established optimization techniques.

The integration of machine learning into optical networks requires more than selecting an algorithm. It requires a data architecture that captures the right features at the right time.

Optical telemetry may be high-volume, noisy, and heterogeneous, with different vendors exposing different management interfaces. Feature engineering must translate raw measurements into meaningful indicators of link health, congestion, and failure risk [22]. Model training also requires representative data, but rare failures and unusual traffic conditions are precisely the cases where prediction matters most. This creates a class imbalance problem and a risk that models will perform well on average while failing during extreme events. Robustness therefore depends on simulation, synthetic data, and careful validation across diverse network conditions [16].

Closed-loop automation is the most ambitious vision for machine learning in wavelength-switched networks. In a closed loop, telemetry feeds a model, the model recommends or executes an action, and the network's response is measured to update future decisions. Such loops can improve spectral efficiency by continuously adjusting modulation, power, and wavelength assignments. They can also improve resilience by detecting degradation and rerouting traffic before service-impacting failures occur. However, closed-loop control raises safety and accountability questions. If an automated action causes a widespread outage, responsibility may be diffuse among model developers, data engineers, network operators, and vendors [18]. Human oversight, rollback mechanisms, and clear escalation paths are therefore essential, especially for actions that affect critical services.

A further challenge is the lifecycle management of machine learning models in infrastructure settings. Models decay as fiber plants age, traffic patterns shift, and hardware is upgraded. A model trained on one network topology may not generalize to another, and even within a single network, seasonal or event-driven changes can alter the data distribution [17]. Retraining must be scheduled without disrupting operations, and models must be versioned, audited, and tested against safety constraints. This resembles the technical debt observed in general machine learning systems, where hidden dependencies and undeclared consumers create fragility [17]. In optical networks, such fragility can translate directly into service outages, making disciplined model governance a core engineering requirement rather than an administrative afterthought.

4. Performance Trade-offs Across Switching, Routing, and Spectrum Allocation

Performance optimization in wavelength-switched networks involves unavoidable trade-offs. Latency can be reduced by establishing direct optical paths, but direct paths may waste spectrum if traffic is sparse. Spectral efficiency can be increased by packing wavelengths tightly, but this leaves less room for protection and restoration. Blocking probability can be lowered by reserving spare capacity, but reservation raises cost and may reduce utilization. Machine learning can help navigate these trade-offs, but it cannot make them disappear. A model that optimizes for average throughput may increase tail latency for latency-sensitive tenants, while a model that optimizes for fairness may reduce aggregate efficiency. The choice of objective function is therefore a policy decision, not merely a technical one.

Routing and spectrum assignment are classic problems in elastic optical networks. The network must choose a route and allocate a contiguous spectrum block that satisfies continuity and contiguity constraints [12]. Classical algorithms often use shortest-path routing with first-fit spectrum assignment, but these heuristics can fragment spectrum and increase blocking. Machine learning can improve decisions by predicting future demand or learning which assignment patterns preserve flexibility [9]. For example, a model might recognize that certain routes are likely to experience growth and therefore avoid fragmenting their spectrum. Alternatively, reinforcement learning can learn a policy that balances immediate requests

against long-term network state. The difficulty is that learned policies may be difficult to interpret and may behave unpredictably outside the training distribution.

Elastic optical networking introduced new dimensions of flexibility, including variable spectrum allocation and distance-adaptive modulation [3]. These capabilities can improve spectral efficiency, but they also increase the complexity of control and management [4]. Machine learning can help manage this complexity by learning relationships between distance, modulation format, and achievable capacity. However, the optical layer is subject to nonlinear effects and aging, so predictions must be updated as conditions change. Space-division multiplexing offers another path to capacity growth by using multiple cores or modes in a fiber [15]. This approach can reduce cost per bit, but it also introduces new coupling and crosstalk effects that machine learning models must account for. The interaction between spatial multiplexing and wavelength switching remains an active area of research and deployment.

Energy consumption is another critical trade-off. Optical switching is generally more energy efficient than electronic switching for large flows, but the overall network energy profile depends on cooling, amplification, and control overhead [14]. Machine learning can reduce energy use by consolidating traffic onto fewer wavelengths, putting unused equipment into low-power modes, or choosing routes that minimize amplification. However, these actions must be balanced against resilience. If too much capacity is consolidated, a single fiber cut may affect many services. Sustainable optimization therefore requires multi-objective models that treat energy, availability, and fairness as co-equal concerns rather than secondary constraints. This is especially important as data center energy use and AI workloads attract greater public scrutiny [14].

5. Infrastructure, Deployment, and Operational Governance

Deploying machine learning in wavelength-switched networks requires significant infrastructure investment. Operators need sensors, telemetry pipelines, data storage, and compute resources for training and inference. They also need skilled personnel who understand both optical networking and machine learning. In many organizations, these skills reside in different teams, creating organizational silos that slow adoption. Software-defined transport architectures can help by providing programmable interfaces and centralized visibility [11]. However, the control plane must be secured against cyberattacks and misconfiguration. A compromised controller or poisoned model could redirect wavelengths, disrupt synchronization, or expose sensitive traffic patterns. Security must therefore be designed into the model lifecycle, not added after deployment.

Operational governance is equally important. Machine learning models should be documented, versioned, and audited. Their recommendations should be explainable enough for network engineers to understand why an action was taken. When models are updated, changes should be tested in simulation or shadow mode before affecting production traffic. Governance should also define who is accountable for model errors and how affected customers will be notified. These requirements resemble emerging AI ethics guidelines that emphasize transparency, accountability, and human oversight [19]. In critical infrastructure, such guidelines are not optional. They are necessary conditions for public trust and regulatory compliance.

Standards and interoperability present further obstacles. Wavelength-switched networks often comprise equipment from multiple vendors, each with proprietary management interfaces and

data models. Machine learning models trained on one vendor's telemetry may not transfer easily to another. Open standards and common data schemas can reduce this friction, but they require coordination among vendors, operators, and standards bodies. Governance must also address data sharing. Network telemetry can reveal sensitive information about traffic volumes, customer locations, and service quality. Privacy-preserving techniques such as aggregation, differential privacy, and federated learning may help, but they introduce trade-offs in model accuracy and operational complexity. Policy makers may need to clarify data ownership and cross-border data flow rules for network telemetry.

6. Robustness, Fairness, and Sustainability

Robustness is a central requirement for any machine learning system that controls critical infrastructure. Optical networks are exposed to physical faults, weather, construction damage, and equipment aging. They are also exposed to adversarial threats, including signal jamming, fiber tapping, and cyberattacks on control systems. Machine learning models can improve anomaly detection and failure prediction, but they can also be fooled by adversarial inputs or confused by distribution shifts [16]. A model trained on normal traffic may fail during a denial-of-service attack or a large-scale event. Robustness testing should therefore include stress scenarios, adversarial examples, and degraded telemetry conditions. Models should also have fallback modes that revert to conservative, well-understood heuristics when confidence is low.

Fairness in wavelength-switched networks is a relatively under-explored but increasingly important concern. If machine learning optimization favors large tenants with predictable traffic, smaller tenants or public-interest services may experience higher latency or lower reliability. If models allocate restoration capacity based on historical revenue, regions with less commercial traffic may be systematically disadvantaged. Fairness can be defined in multiple ways, including equal access, proportional service, or priority for critical services. The choice of fairness metric should be made transparently and involve stakeholders beyond network operators. In municipal or community networks, for example, residents may expect equitable service regardless of profitability [18]. Machine learning systems should therefore include fairness constraints or post-processing methods that prevent discriminatory outcomes.

Sustainability adds another layer of complexity. Data centers and communication networks consume significant energy, and the training of large machine learning models can itself be carbon-intensive [20]. Wavelength-switched networks can reduce energy use by avoiding unnecessary electronic processing, but they also require cooling, amplification, and control overhead. Machine learning can help by shifting traffic to lower-carbon routes, powering down unused equipment, and predicting demand to avoid overprovisioning. However, these benefits must be measured over the full lifecycle of equipment, including manufacturing and disposal. Sustainability metrics should include embodied carbon, not just operational energy. Policy makers may require environmental reporting for network infrastructure, and operators may need to balance sustainability goals with resilience and affordability.

7. Case Illustrations and Cross-Domain Comparisons

Intra-data center networks provide a compelling case for machine learning enabled wavelength switching. Machine learning training clusters generate synchronized, high-bandwidth flows that can benefit from optical circuit switching and low-latency interconnects [6]. Wavelength-switched clock-synchronized interconnects using hollow-core fiber can reduce latency and improve synchronization for distributed workloads [7]. A machine

learning controller could predict job placement, allocate wavelengths to reduce contention, and reconfigure the optical fabric as workloads migrate. However, the controller must coordinate with job schedulers, storage systems, and power management. If the model optimizes only network metrics, it may create bottlenecks elsewhere. Cross-layer optimization is therefore necessary but difficult because it requires data sharing across domains that are often managed separately.

Wide-area backbone networks offer a different context. Here, traffic is aggregated from many sources, and failures can affect millions of users. Machine learning can assist with traffic forecasting, failure localization, and restoration planning. Software-defined transport controllers can provide the programmability needed to act on model recommendations [11]. Yet backbone networks are regulated and subject to strict service-level agreements. Automated actions must be auditable and reversible. In this setting, machine learning is more likely to be used for decision support than for fully autonomous control, at least in the near term. Hybrid approaches that combine human expertise with model recommendations may offer the best balance of performance and accountability.

Cross-domain comparisons can illuminate governance and design choices. Power grids use machine learning for load forecasting and fault detection, but they retain strict engineering standards and human operators in the loop. Air traffic control uses automation for scheduling and conflict detection, but ultimate authority remains with human controllers. These examples suggest that critical infrastructure tends to adopt automation gradually, with clear boundaries between advisory and executive functions [18]. Wavelength-switched networks are likely to follow a similar path. The most successful deployments may be those that start with bounded use cases, such as quality-of-transmission prediction or energy-aware routing, and expand autonomy only after demonstrating reliability. This incremental approach also allows organizations to build data pipelines, governance processes, and workforce skills.

Computing trends reinforce the need for long-term planning. The slowing of Moore's Law has increased interest in specialized architectures and optical interconnects [13]. As computation becomes more distributed, the network becomes a critical resource rather than a passive conduit. Machine learning can help manage this resource, but it also increases demand for computation and data movement. The result is a feedback loop: better networks enable more machine learning, and more machine learning creates new requirements for network performance. Managing this loop requires system-level thinking that considers energy, economics, and equity. It also requires collaboration between optical engineers, computer scientists, economists, and policy makers [22].

8. Policy Implications and Forward-Looking Perspectives

Policy makers have a role in shaping how machine learning is used in wavelength-switched networks. They can support research and development, fund testbeds, and encourage open standards. They can also set rules for transparency, accountability, and environmental reporting. AI ethics guidelines increasingly call for human oversight, non-discrimination, and explainability [19]. These principles should be adapted to network infrastructure, where outages can have immediate social and economic consequences. Regulators may require operators to disclose how automated decisions affect service quality, especially for essential services such as healthcare, education, and emergency response. They may also need to address liability when automated optimization causes harm.

International coordination will be necessary because optical networks cross borders and carry global traffic. Data protection rules, competition policy, and cybersecurity regulations differ across jurisdictions, creating compliance challenges for operators that use shared machine learning platforms. Standards bodies can help by developing common vocabularies for model documentation, telemetry exchange, and safety assurance. Professional societies can promote best practices for model validation and incident reporting. Universities can contribute by training a workforce that understands both optical systems and responsible machine learning. The goal should be an ecosystem in which innovation is encouraged but risks are managed.

Looking forward, several research directions are promising. Federated learning could allow operators to train models without sharing sensitive telemetry. Digital twins could provide safe environments for testing reinforcement learning policies before deployment. Explainable AI could help engineers understand why a model recommends a particular wavelength assignment. Multi-objective optimization could balance latency, energy, fairness, and resilience in a transparent way. However, these advances will not deliver benefits automatically. They require sustained investment, interdisciplinary collaboration, and governance frameworks that keep human welfare at the center. Machine learning should be viewed as a tool for enhancing wavelength-switched network performance, not as a substitute for sound engineering and public accountability.

9. Conclusion

Machine learning enabled performance optimization of wavelength-switched networks offers significant opportunities for improving latency, spectral efficiency, resilience, and energy management. By learning from telemetry and adapting to changing conditions, models can help operators manage the complexity of elastic spectrum, dynamic traffic, and multi-vendor infrastructure. However, the benefits are conditional. Optimization must be embedded in robust control architectures, supported by high-quality data, and governed by clear accountability mechanisms. It must also respect the physical limits of optical systems and the social expectations placed on critical infrastructure. Trade-offs among efficiency, fairness, robustness, and sustainability cannot be resolved by algorithms alone. They require deliberate choices about objectives, constraints, and who participates in decision-making.

The paper has argued that wavelength-switched networks should be understood as socio-technical systems in which machine learning is one component among many. Architectural choices, deployment practices, governance policies, and environmental considerations are not externalities but constitutive elements of performance. Intra-data center interconnects illustrate the potential for low-latency optical switching, while backbone networks reveal the need for auditability and human oversight. Cross-domain comparisons with power grids and air traffic control suggest that incremental autonomy is likely to be more successful than rapid full automation. Future work should focus on multi-objective optimization, explainability, federated learning, and sustainability metrics. If these directions are pursued responsibly, machine learning can help wavelength-switched networks meet the demands of the coming decade without sacrificing resilience, equity, or public trust.

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