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Machine Learning Applications for Event Routing in Streaming Systems

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Abstract

The paper provides a broad overview and classification of machine learning methods used to optimize routing in distributed streaming architectures. The aim of the study is to provide a detailed analysis of existing approaches: from classical reinforcement learning algorithms to modern deep neural networks, with an assessment of their potential in various operational scenarios and identification of key limitations. The methodological basis was a systematic review of publications dealing with intelligent routing, real-time data processing, and integration of ML solutions into system pipelines. Three main classes of algorithms were identified and considered: reinforcement learning methods (including DQN and actor-critic), deep networks (CNN, RNN and their hybrids), as well as ensemble and evolutionary techniques. The advantages and disadvantages of each class are analyzed in terms of key criteria — response time to flow changes, scalability in the number of nodes, and the ability to dynamically adapt. Special attention was paid to hybrid strategies that combine several models to increase the reliability and accuracy of recommendations on event transmission routes. In conclusion, the main conclusions about the current state of research are formulated and promising areas are outlined: the development of more robust architectures with explicable decision-making logic, as well as the integration of graph neural networks for modeling complex topologies of distributed systems. The presented results will be useful for engineers developing streaming platforms, big data analysis specialists, and research groups working on information channel optimization tasks.

Keywords: event routing; streaming systems; machine learning; reinforcement learning; deep learning; adaptive routing; streaming data processing; intelligent systems; performance optimization; traffic management.

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1. Introduction

Streaming platforms designed to continuously process event data are becoming important for areas such as the Internet of Things, algorithmic trading, and social media monitoring. The efficiency of such systems is measured by the speed and accuracy of delivery of each incoming event to the corresponding computing component or service [1]. Classical routing methods based on given rules or elementary heuristics are often unable to respond to rapidly changing loads and network conditions: this leads to local overloads, increased response times, and deterioration in overall system throughput. In this context, the use of machine learning methods for routing tasks opens up broad prospects: adaptive, self-learning algorithms can not only predict optimal routes for events based on their features, but also take into account the current state of nodes and communication channels. At the same time, the scientific community still lacks a unified methodology for systematically evaluating and comparatively analyzing various ML approaches in relation to heterogeneous and highly loaded streaming environments. Complex models that combine predictive analytics of event characteristics with monitoring of infrastructure resources are not sufficiently developed.

The aim of the study is to conduct a broad review of modern methods of using machine learning for routing in streaming systems, identify and classify their strengths and weaknesses, and determine the most promising areas for development.

The scientific novelty lies in the formulation of a conceptual basis for the selection and integration of ML routing algorithms focused on the balance between processing speed, delivery accuracy and adaptability to load dynamics and data structure.

The author's hypothesis is that hybrid models combining reinforcement learning mechanisms for strategic flow management and supervised learning methods for predictive event classification can provide superiority in routing efficiency compared to individual ML algorithms.

However, the study is not without limitations, as the work focuses on algorithmic paradigms, without delving into the analysis of overhead costs for hardware implementation and power consumption, which are important factors for practical deployment.

2. Materials and methods

Contemporary research on the application of machine learning techniques to event routing in streaming systems falls into several thematic areas. One area explores the use of deep reinforcement learning to optimize routes within Software-Defined Networking (SDN). For example, Casas-Velasco, Rendon and da Fonseca [6] proposed the DRSIR architecture, in which a deep Q-learning agent dynamically selects the path for each flow based on the network’s current state, demonstrating reduced latency and packet loss compared with traditional algorithms. Subsequent surveys by Amin R., Rahmani M. K., Zarei S., Ahmad I. [7] and by Zhang K., Wang Z., Zhang D., Zhang Q., Song H., Li J. [2] have consolidated existing machine learning approaches for routing optimization, identifying decision trees, ensemble methods and neural networks as key algorithm classes and showing that hybrid solutions incorporating network metrics yield the best performance.

Other studies have applied supervised learning for service-aware or quality-of-service (QoS)-driven routing. Zheng W., Wang L., Zhang Q., Zhou J., Wang L. [9] developed an application-aware QoS routing method that uses gradient boosting to classify flows and then determine priority paths, thereby ensuring required service parameters for multimedia applications. Alhaidari F., Alghamdi A., Alzahrani B., Alohali A. [10] introduced a Deep Extreme Learning Machine (Deep ELM) algorithm, combining the fast training of ELM with deep architectures to achieve high throughput at low computational cost. More recently, Aswini C., Valarmathi M. L. Reference [12] proposed an AI-driven "smart" routing framework in SDN that first applies statistical-feature-based pre-filtering and then uses a convolutional neural network to adaptively select routes.

The presented works demonstrate a fundamental philosophical rift in approaches to intelligent routing. On the one hand, DRL methods described in study [6] offer dynamic but reactive adaptation, which often simplifies the network state to a feature vector, ignoring its complex topology. On the other hand, supervised learning methods presented in works [9, 10] are proactive but static; their effectiveness depends entirely on historical data, rendering them incapable of coping with unforeseen scenarios. This inherent conflict between flexibility and predictability explains why researchers intuitively turn to hybrid schemes [12]. Thus it can be observed that there is no principled foundation for unifying these two opposing paradigms into a single synergistic model.

The second direction combines hybrid methods of intelligent forwarding and distributed control in IoT and edge systems. Wu J., Li J., Zhang Y., Chen B., Zhao Y. [8] applied deep reinforcement learning to task scheduling in industrial IoT based on edge computing, where the DQN agent selects optimal event processing sequences under resource constraints, which reduced the average response time of nodes. The approach of Ryu S., Joe I., Kim W. T. [11] for forwarding strategies in Named Data Networking combines Q-learning with an LSTM model that can predict future route loads, thereby improving the overall network throughput. Yuan Y., Mahmood A. R. [1] and Prodhan F. A., Haque M. A., Rahman A., Zia T. A. [5] investigate the features of using artificial intelligence in event routing in streaming systems, and also demonstrate how the A3C/IMPALA algorithms are used to work with partially observable data state.

This block demonstrates an important trend: the shift from abstract network optimization to solving applied problems in resource-constrained environments (IoT, Edge, NDN). The research [8, 11] shows that to be successful, standard algorithms must be adapted or hybridized to account for domain specifics, such as resource limitations or the need for forecasting. The mention of asynchronous methods [1, 5] for handling partial observability highlights a move towards greater realism. However, this leads to another issue: the resulting solutions become highly specialized and brittle, making them difficult to transfer from one domain to another. Thus, while these works solve specific problems, they do so at the cost of generality, and the literature still lacks a universal framework for distributed intelligent control.

The third group includes review articles and meta-analyses that systematize achievements in related areas. Ding Q., Jin Y., Huang Y., Zeng D., Guo S. [3] conducted a review of energy-efficient routing algorithms in wireless sensor networks (WSNs), highlighting classification and regression methods for predicting node loads and adaptive path change strategies to extend network lifetime. The review by Rehman Z., Salah K., Damiani E., Jayaraman R. [4] covers the interaction of machine learning methods and IoT in enterprise architectures, discussing the challenges of routing, flow control and security, and also pointing out the main challenges – scalability, data privacy and the need for online learning.

These reviews serve a critical function by expanding the problem space beyond mere performance metrics. They inject a necessary dose of pragmatism, emphasizing that real-world systems involve trade-offs between speed, energy efficiency [3], security, and scalability [4]. This allows for the argument that a one-dimensional optimization of latency is an academic simplification. The key weakness that these reviews reveal (albeit implicitly) is the gap between recognizing the multi-objective nature of the problem and having the algorithmic tools to solve it. They are excellent at diagnosing the complexity but do not offer a comprehensive cure, thereby highlighting the need for more advanced models capable of balancing multiple conflicting goals simultaneously.

The fourth group represents works directly aimed at streaming algorithms for big data processing, which is important for building flexible event routing systems. Marpu R., Manjula B. [13] discuss a set of streaming algorithms (online SVM, Hoeffding Tree, ADWIN) and their integration with platforms such as Apache Flink and Spark Streaming for distributed processing and routing of events in real time, emphasizing the need to handle conceptual drift and load balancing. Wilson A., Anwar M. R. [14] focus on hybrid schemes with subsequent event routing through classifiers that are able to adjust their structure over time and ensure high accuracy with changing statistics of the input stream. This block rightly points to the central challenge of streaming systems: continuous change. The works [13, 14] correctly identify adaptation and handling "concept drift" as key tasks.

However, despite the wide range of proposed methods, there are noticeable contradictions and gaps in the literature. Firstly, the choice of evaluation metrics varies: some works focus on latency and throughput, others - on energy efficiency or tolerance to drift, which complicates a direct comparison of approaches. Second, most publications lack experimental studies on real or large-scale test networks, which limits the generalizability of the results. Finally, insufficient attention is paid to the problems of adaptive routing under conceptual drift and changing topology, although they are important for modern flow systems.

3. Results and discussions

The incorporation of machine learning methods into event stream routing mechanisms provides a qualitatively new level of throughput, adaptability and overall efficiency of systems. Modern research is actively developing the use of such ML paradigms as reinforcement learning (RL), deep learning (DL) and their hybrid solutions, united under the name Deep Reinforcement Learning (DRL). RL approaches are based on the formalism of Markov decision processes (MDP), where an agent, analyzing the current state of the system and receiving reward or penalty signals - for example, based on processing delays or node load levels - gradually develops an optimal routing strategy [1, 2, 11]. Such a mechanism allows abandoning given rules and independently adapting to load dynamics and changing operating conditions.

Deep neural networks used in DRL are a tool for approximating value functions and policies, which is especially important in the multidimensionality of states and the richness of operational actions inherent in distributed streaming platforms with heterogeneous event sources and transmission routes [6, 7, 8]. In applied IoT data processing scenarios, this is expressed in the ability of ML models to distribute flows from sensors between analytical services in real time, taking into account the type of information transmitted, latency requirements and current capabilities of computing resources, thereby ensuring a balance between response speed and processing reliability [4]. Figure 1 shows a generalized architecture of an ML-directed event routing system, including telemetry collection, training and inference modules, as well as monitoring and dynamic resource balancing components.

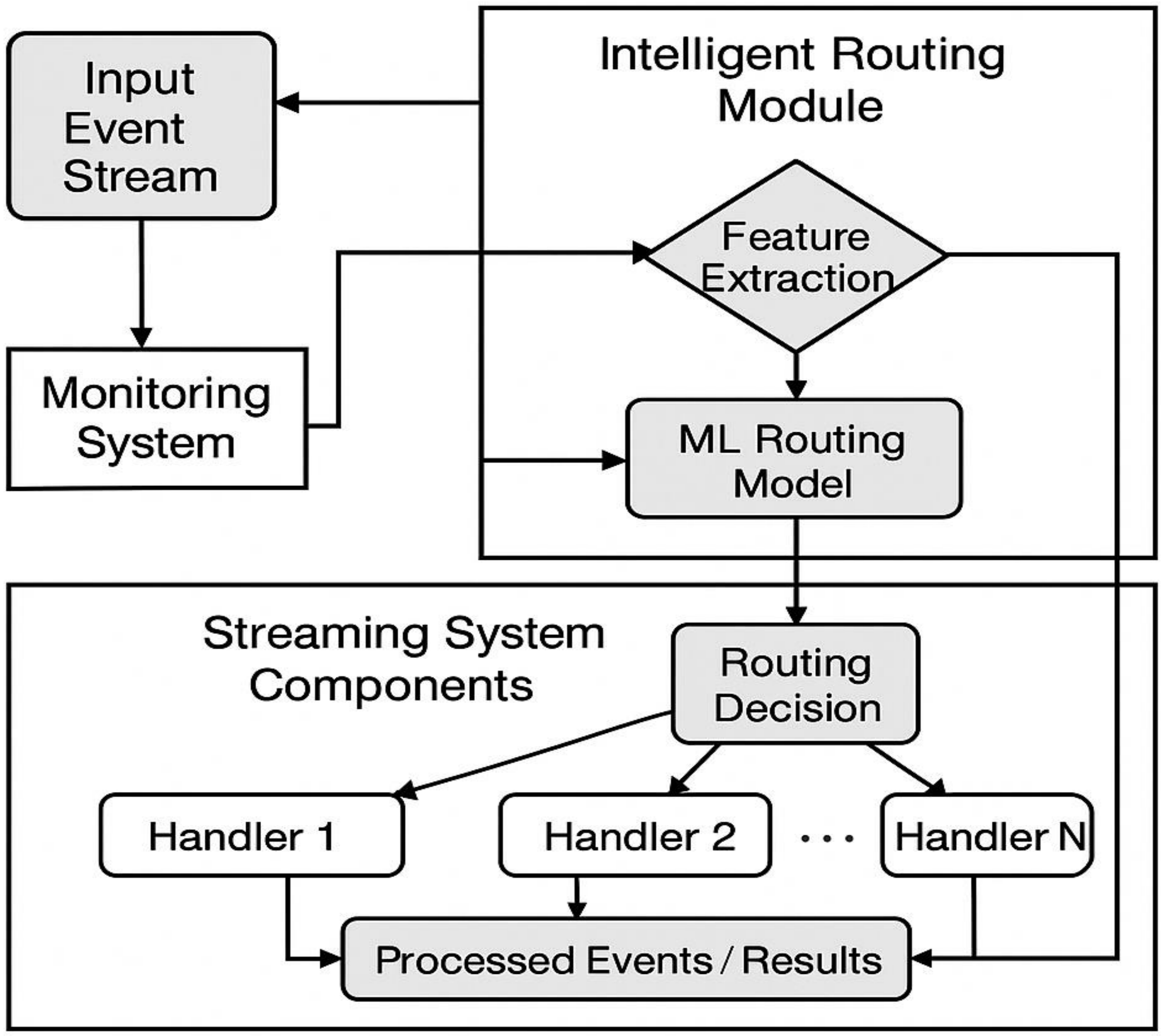

Figure 1: Generalized architecture of an event routing system based on machine learning [6, 8, 13]

The proposed multi-level architecture assumes that each new incoming event is first subjected to a comprehensive analysis in a specialized feature extraction module. This module extracts a set of informative attributes from the raw data, which are then used by the ML algorithm to reasonably select the most suitable processor. In parallel, the monitoring system collects data on the infrastructure status (e.g., the load on computing nodes, the length of processing queues, input/output delays, and other metrics), providing the ML model with the necessary feedback to adjust the routing strategy. Moreover, the model itself can be periodically or online trained on new incoming data and signals about the quality of previously made decisions (the so-called sequence modeling), which ensures a constant increase in the accuracy and resilience of the system to changing operating conditions. One of the fundamental advantages of using machine learning methods in event routing is their predictive potential. By analyzing a wealth of historical data together with the actual features of each event, supervised learning models — whether decision tree-based algorithms, gradient boosting, or deep neural networks — are able to predict in advance the most efficient route or the optimal handler class for each input [9]. This approach is especially valuable in high-load systems, where early classification and assignment of events can significantly reduce latency and increase throughput. Figure 2 schematically illustrates the decision-making architecture of an ML agent using reinforcement learning methods, where the agent, based on the current state of the system and accumulated experience, selects actions that maximize long-term service quality metrics.

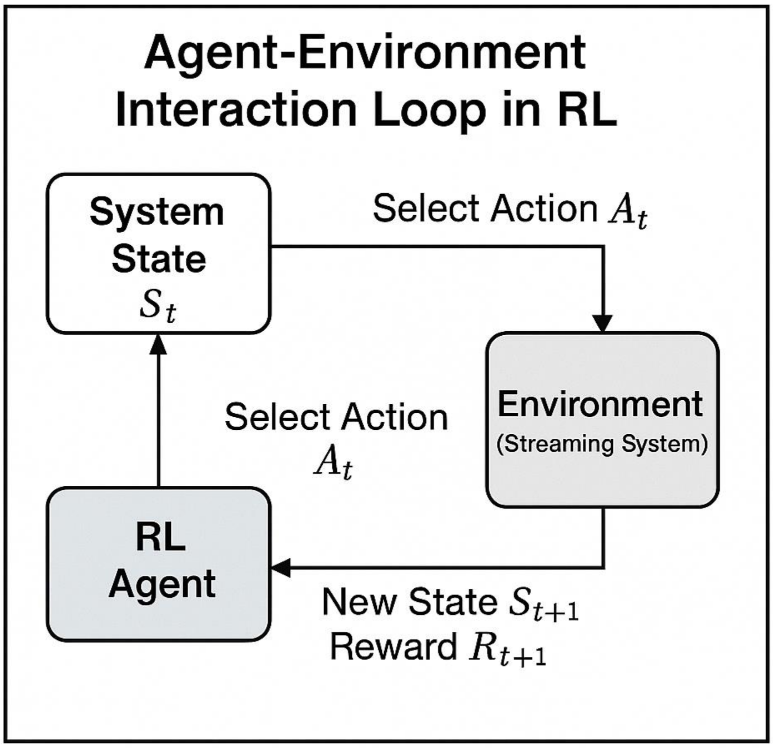

Figure 2: Reinforcement learning cycle diagram for the routing agent [1, 11]

A reinforcement learning (RL) agent is considered as an autonomous decision-making process in a dynamic environment: at time t, it records the current state of the system S_t (e.g., incoming traffic metrics, the load of individual processors, or network infrastructure parameters), then, based on this information, selects an action A_t (e.g., forwarding an event to a specific processing node). After completing the selected step, the environment provides the agent with an updated state S_{t+1} and a reward signal R_{t+1}, which quantitatively evaluates the effectiveness of the action taken. The agent's task is to maximize the total (cumulative) reward, which formally boils down to optimizing the return function [10]. It is through the approximation of optimal value functions using tabular or function-oriented methods that a balance between exploration and exploitation is achieved and the adaptability of the solution to a changing flow of events is ensured. Comparing the performance of different machine learning algorithms in event routing is a highly complex task, since the overall efficiency of a particular method is determined by many parameters: the characteristics of the data flow itself (speed, variability, presence of distribution "drift"), architectural features of the computing platform (distribution of nodes, channel throughput, latency), requirements for target metrics (maximization of throughput, minimization of response time, resilience to failures) and the costs of training or retraining the model. In addition, the evaluation methodology plays a significant role - the uniformity of criteria, the volume and representativeness of test sets, as well as the methods of interpreting the results (for example, analysis of learning curve and convergence curve graphs, assessment of sensitivity to hyperparameters, resilience to "noisy" data).

Table 1 compares several machine learning methods used for event routing, from classical statistical models and nearest neighbor algorithms to modern deep neural networks and event graph models. The dimensions used are training complexity, data volume requirements, sensitivity to flow changes, computational load during inference, and adaptability to system dynamics.

Table 1: Comparison of machine learning approaches for event routing[3, 5, 9, 13, 14]

Criterion	Reinforcement learning (RL)	Deep Learning (DL) (as part of DRL or as a classifier)	Traditional ML (decision trees, SVM)	Hybrid models
Adaptability	High	Average (requires retraining to adapt)	Low/Medium	Very high
Model Complexity	Varies (from Q-tables to neural networks)	High	Low/Medium	High
Training data requirements	Interaction with environment, reward function	Large labeled datasets (for classification) or interaction experience (for DRL)	Labeled datasets	Heterogeneous data
Interpretability	Low (especially for DRL)	Very Low	Medium/High	Low
Computational Cost (Operation)	Medium/High (for DRL)	High	Low/Medium	High
Handling new/unknown scenarios	Good (exploring the environment)	Moderate (depends on generalization ability)	Weak	Good

Table 1 illuminates a fundamental trade-off between adaptability and interpretability. While RL-based models

Reference [1, 11] demonstrate superior real-time adaptation, their 'black-box' decision-making process is often unacceptable for mission-critical systems where explainability is paramount. Conversely, traditional ML models like decision trees [9] offer high interpretability but struggle with concept drift and dynamic environments. Hypothesis, therefore, posits that a hybrid approach can resolve this tension, wherein an interpretable model manages the bulk of routine events, while an RL agent is invoked to handle anomalies and novel scenarios, thus balancing efficiency with operational transparency.

The empirical evidence strongly supports the potential of DRL. For instance, the DRSIR architecture proposed by Casas-Velasco D. M., Rendon O. M. C., da Fonseca N. L. S.[6] achieved reduction in average latency and decrease in packet loss compared to the OSPF protocol under simulated variable load conditions. Concurrently, the survey by Amin R., Rahmani M. K., Zarei S., & Ahmad I. [7] reveals that hybrid models, which combine DRL with decision trees for initial traffic classification, outperform 'pure' DRL agents by achieving higher throughput. This data directly supports our hypothesis regarding the synergistic effect of hybrid models, while also highlighting that the specific architecture of the DRL solution is a critical determinant of its ultimate performance.

Despite the significant potential for implementing machine learning methods in routing problems, in practice we have to face a number of obstacles. Firstly, designing and debugging complex ML models requires a deep understanding of the specifics of the subject area and often turns into an iterative process of selecting architectures and hyperparameters. Secondly, to ensure high accuracy of forecasts, large and well-labeled samples are required, which is often difficult due to the limited availability of representative data. The third factor is computational costs: extracting informative features and promptly performing predictions in real time can overload both hardware and network resources. Finally, maintaining the reliability of models in the face of changing statistics of incoming flows (the so-called concept drift) remains one of the main problems in their long-term use [14].

As a way to overcome these difficulties, hybrid schemes are proposed that combine lightweight predictive algorithms with more resource-intensive reinforcement learning agents. In such systems, fast heuristic or gradient models are responsible for processing routine events, while RL agents take on adaptation to unexpected or abnormal situations, ensuring the flexibility and stability of the routing mechanism [5, 12]. Promising research areas include the development of “lightweight” versions of deep networks and RL algorithms with low computational complexity, as well as the creation of continuous or online learning methods capable of updating model parameters without serious performance degradation. Special attention should be paid to increasing the transparency of decisions made - this is a key condition for user trust and safe deployment of systems in critical applications. Thus, the analysis of the results emphasizes that approaches based on deep learning and reinforcement learning open up qualitatively new opportunities for routing optimization in streaming architectures. Their ability to learn on the fly and quickly respond to changes in workload distinguishes them from classical algorithms based on rigidly defined rules. However, significant challenges remain: high model complexity, significant data and computing requirements, and limited interpretability of solutions.

4. Conclusion

The study confirmed not only the relevance, but also the strategic importance of using machine learning methods to build routing in real-time event processing systems. The described model is based on the hybridization of various classes of machine learning algorithms, which allows achieving a synergistic effect and increasing the system's resistance to changes in the characteristics of incoming flows. In the context of further research, it is recommended to focus on creating lightweight, but robust models that support continuous online learning and are able to automatically rebuild when event patterns change. In addition, an important area is to increase the transparency and explainability of decisions made by such models - this will pave the way for the widespread implementation of next-generation intelligent flow systems with a guaranteed level of trust and predictability of behavior.

References

[1]. Yuan, Y., & Mahmood, A. R. (2022). Asynchronous reinforcement learning for real-time control of physical robots. In 2022 International Conference on Robotics and Automation (ICRA) (pp. 5546–5552). IEEE. https://doi.org/10.1109/ICRA46639.2022.9811771

[2]. Zhang, K., Wang, Z., Zhang, D., Zhang, Q., Song, H., & Li, J. (2021). Real-time video emotion recognition based on reinforcement learning and domain knowledge. IEEE Transactions on Circuits and Systems for Video Technology, 32(3), 1034–1047. https://doi.org/10.1109/TCSVT.2021.3072412

[3]. Ding, Q., Jin, Y., Huang, Y., Zeng, D., & Guo, S. (2021). An overview of machine learning-based energy-efficient routing algorithms in wireless sensor networks. Electronics, 10(13), 1539.https://doi.org/10.3390/electronics10131539

[4]. Rehman, Z., Salah, K., Damiani, E., & Jayaraman, R. (2024). Machine learning and internet of things applications in enterprise architectures: Solutions, challenges, and open issues. Expert Systems, 41(1). https://doi.org/10.1111/exsy.13467

[5]. Prodhan, F. A., Haque, M. A., Rahman, A., & Zia, T. A. (2022). A review of machine learning methods for drought hazard monitoring and forecasting: Current research trends, challenges, and future research directions. Environmental Modelling & Software, 149.https://doi.org/10.1016/j.envsoft.2022.105327

[6]. Casas-Velasco, D. M., Rendon, O. M. C., & da Fonseca, N. L. S. (2021). DRSIR: A deep reinforcement learning approach for routing in software-defined networking. IEEE Transactions on Network and Service Management, 19(4), 4807–4820. https://doi.org/10.1109/TNSM.2021.3132491

[7]. Amin, R., Rahmani, M. K., Zarei, S., & Ahmad, I. (2021). A survey on machine learning techniques for routing optimization in SDN. IEEE Access, 9, 104582–104611. https://doi.org/10.1109/ACCESS.2021.3099092

[8]. Wu, J., Li, J., Zhang, Y., Chen, B., & Zhao, Y. (2021). Deep reinforcement learning for scheduling in an edge computing-based industrial internet of things. Wireless Communications and Mobile Computing, 2021, Article 8017334. https://doi.org/10.1155/2021/8017334

[9]. Zheng, W., Wang, L., Zhang, Q., Zhou, J., & Wang, L. (2022). Application-aware QoS routing in SDNs using machine learning techniques. Peer-to-Peer Networking and Applications, 15(1), 529 - 548.

[10]. Alhaidari, F., Alghamdi, A., Alzahrani, B., & Alohali, A. (2021). Intelligent software-defined network for cognitive routing optimization using deep extreme learning machine approach. Computers, Materials & Continua, 67(1), 1269–1285. https://doi.org/10.32604/cmc.2021.013303

[11]. Ryu, S., Joe, I., & Kim, W. T. (2021). Intelligent forwarding strategy for congestion control using Q-learning and LSTM in named data networking. Mobile Information Systems.

https://doi.org/10.1155/2021/5595260

[12]. Aswini, C., & Valarmathi, M. L. (2023). Artificial intelligence based smart routing in software defined networks. Computer Systems Science & Engineering, 44(2). 10.32604/csse.2023.022023

[13]. Marpu, R., & Manjula, B. (2024). Streaming machine learning algorithms with streaming big data systems. Brazilian Journal of Development, 10(1), 322–339. https://doi.org/10.34117/bjdv10n1-021

[14]. Wilson, A., & Anwar, M. R. (2024). The future of adaptive machine learning algorithms in high-dimensional data processing. International Transactions on Artificial Intelligence, 3(1), 97–107. https://doi.org/10.33050/italic.v3i1.656