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AI-Assisted Framework for Green-Routing and Load Balancing in Hybrid Software-Defined Networking: Proposal, Challenges and Future Perspective

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ABSTRACT The explosive growth of IP networks, the advent of cloud computing, and the rapid progress in wireless communications witnessed today reflect significant progress towards meeting the explosive data traffic demands. Consequently, communications service providers should deploy efficient and intelligent network solutions to accommodate the huge traffic demands and to ease the capacity pressure on their network infrastructure. Besides, vendors should develop novel energy-efficient networks to reduce network utility costs and carbon footprint. Software-defined networking (SDN) provides a suitable solution, however, complete SDN deployment is currently unachievable in the short-term. An alternative is the hybrid SDN/open shortest path forwarding (OSPF) network, which allows the deployment of SDN in legacy networks. Nevertheless, hybrid SDN/OSPF also faces several technical, economic and organizational challenges. Although many energy-efficiency routing solutions exist in hybrid SDN/OSPF networks, they are generic and reactive by design. Moreover, these solutions are characterized by manual control plane forwarding configurations, leading to sub-optimal performance. The recent promising combination of SDN and artificial intelligence (AI) techniques such as machine learning (ML) and deep learning (DL) in traffic management and control provides tremendous opportunities. In this paper, we first provide a review of the most recent optimization approaches for global energy-efficient routing and load balancing. Next, we investigate a scalable and intelligent integrated architectural framework that leverages deep reinforcement learning (DRL) techniques to realize predictive and rate adaptive energy-efficient routing with guaranteed quality of service (QoS), in transitional hybrid SDN/OSPF networks. Based on the need to minimize global network energy consumption and improve link performance, this paper provides key research insights into the current progress in hybrid SDN/OSPF, ML and AI in the hope of stimulating more research.

INDEX TERMS Hybrid SDN/OSPF, traffic engineering, energy-aware routing, quality of service, scalable, machine learning, artificial intelligence, and deep reinforcement learning.

I. INTRODUCTION

A. BACKGROUND

During the last several years, there has been a drastic increase in data traffic volumes because of the changing manner in which information products are created, shared and communicated by the digital society. Statistically, the prediction from recent Cisco Visual Networking Index (VNI) [1] reveals that there will be a threefold rise in IP and Internet traffic by 2022. Besides, the daily use of the Internet is estimated to hit 2.6 Exabytes. This projection indicates a consolidated annual Internet traffic growth rate of 30%. Therefore, it has become

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a matter of necessity to expand wired and wireless networks to accommodate the current growth in traffic demand and the need for efficient and intelligent use of scarce network resources, to optimize network performance. The explosive growth of IP networks, the advent of cloud computing, and the rapid progress in wireless communications witnessed today reflect significant progress towards meeting the explosive data traffic demands. In the current condition of network evolution, mainly characterized by the rising user traffic demands and progressive expansion of network deployment, there are two major issues that arise. First, the aforementioned traffic demand condition has overstretched the capabilities of core network domain of communication network service providers such as Mobile Network Operators (MNOs) and Internet Service Provider (ISPs) to the boundaries. Second, in the current condition of network expansion, MNOs and ISPs cannot circumvent redundant network infrastructure. The unavoidable redundant network infrastructure has led to unnecessary network operational expenditure, and resource and cost waste [2]. Precisely, network energy consumption has rapidly increased. Given the economic and environmental concerns, the environmental and regulatory authorities have put demands on communications service providers to embrace energy-efficient solutions.

Recently, the need for green networking in the information and communications technology (ICT) sector has become more important owing to its impacts [3] and the potential economic benefits [4]. First, various research works have indicated the massive devastating effect of Green House Gases (GHG) emissions and their ramifications on climate change [5]. The ICT sector is reported to produce nearly 20% of the overall human-borne emissions [6]. This trend is estimated to worsen given the rapid developments witnessed in the ICT sector [7]. The energy consumption from the ICT sectors is envisaged to grow steadily over overtime [8]. Second, from an economic perspective, embracing energy-efficient networking can help communications service providers reduce expenditure on their extensive network infrastructures. Essentially, existing network architectures are designed to accommodate peak traffic loads and survivability of service provisioning during degraded network periods. This leads to low efficiency, since in the long term, the network infrastructure is under-utilized, under normal network operations [9]. Besides, existing algorithmic approaches for network operation management and control are energy-unaware. Such approaches include network traffic load balancing [10] and bandwidth minimization [11]. These approaches disregard network resources such as nodes and link operational energy utilization condition.

Given the above considerations, the need to employ energy-efficient algorithmic approaches in the design of communication networks has become significant. Recently, the advances in green networking have enabled the use of improved communication systems, to reduce network energy expenditures. The technologies are employed at different layers of the networking architecture. Such green networking technologies include adaptive link rates which is employed at the data link layer to reduce the link speed during moments of link underutilization [9], [12], and interface proxing employed at the application layer [13], as well as energy-aware application employed at the transport layers [14].

B. MOTIVATION

Over the years, green networking has steadily improved because of the various energy-efficient algorithmic approaches developed. Although these algorithmic approaches have been used in traditional networks, they are unsuitable for modern networks due to certain limitations. Primarily, modern networks are characterized by intense uncertainties and dynamicity in traffic flow trends, and the operating circumstances of networking devices such as routers, network topology and the status of wireless channels. These diverse characteristics can potentially complicate the use of existing approaches in the management and control of modern networks. Therefore, novel algorithmic approaches should be developed to address the concerns.

Traffic engineering (TE) [15], aims to optimize network performance, through dynamic measurement and analysis of real-time network traffic, and is concerned with the design of optimal flow forwarding and routing policies, to fulfill QoS requirements for traffic flows with large volumes. mportant performance metrics considered in TE include throughput, bandwidth, jitter, packet delay and path failure. TE solutions are categorised into heuristic algorithms (HA), model-driven optimization algorithms and model-free optimization. Some of the HA in common use include OSPF and border gateway protocol (BGP) [16]. In general, HA are primarily based on shortest path routing protocols.

Previously, fast HA were proposed to achieve cost-effective energy-aware routing (EAR) and load balancing with QoS guarantees, but optimization efforts in a dynamic scenario can be a challenge. Although HA are simple to apply, they cannot deliver optimalend-2-end (E2E) TE performance.Basically, using such algorithms can complicate the trade-off between energy savings and QoS guarantees, hence degrading network performance.

To overcome the above limitations, dynamic HA been proposed but such algorithms can only support limited network optimization policies [16]. Most existing conventional networks employ dynamic HA, but given the lack global network visibility, they can barely provide high data traffic and ensure the delivery of reliable services. This leads to poor network operations management and control. This condition can potentially compromise dynamic network optimization efforts. Clearly, existing dynamic HA employ a limited range of network optimization policies, and this can hinder their capacity to fully adapt to the ever-changing link patterns. They lack the capacity to robustly redirect and route requests in an energy efficient manner, without experiencing network performance degradation.

Besides, various model-driven optimization approaches have been devised for communication networks. Model-driven approaches are based on network utility maximization (NUM) architecture, where the constrained maximization problem of the utility function is used to formulate the TE problem [17], [18]. There are several limitations pertaining the use of model-driven optimization solutions. Primarily, model-driven solutions are based on the strong assumptions pertaining to the network architecture. Such network architectures include per-flow queuing configuration per-flow queuing configuration for each link, unlimited buffer size per queue, restricted configuration with respect to traffic arrivals and the immediate access of the link rates. However, these assumptions do not hold in real-life networks. Next, they cannot be mathematically represented as explicit functions of TE control parameters. Such parameters are traffic flow splitting ratio for the respective output path link. Lastly, they are not suitable for dynamic time-varying network scenarios, with ever-changing traffic demand trends. Because of the above limitations, these model-based optimization solutions are not implemented in TE to handle practical multi-hop communication networks.

To address the aforementioned concerns, two promising alternatives come to the fore. First, the Software-Defined Networking (SDN) architecture [19] is envisioned to provide a suitable solution, given its unique characteristics. Second, the recent progress in ML and DRL techniques have proved to surpass human level performance in addressing extensive online control tasks. The motivation is to jointly leverage the unique capabilities of the technological advances to deliver the much desired levels of efficiency in network operations management and control. Provided next is a discussion of the above technologies in the scope of current and future communication networks.

SDN refers to the technique that divides the control plane from the data planes transmitting components, resulting into enhanced programmability and integrated flexibility control benefit in computer-based communication networks [19]. SDN technology provides various benefits including enhanced configuration of networks, the ability to support innovation in addition to better performance. Besides, decisions such as routing and scheduling of traffic flows which are secluded from the network forwarding devices, particularly switches are supported, allowing the required decisions to be improved, reconfigured and optimized through a centralised controller [20]. However, for communications service providers, complete SDN deployment is presently unachievable in the immediate term because of financial, technical and organizational challenges. In this condition, a favoured option is hybrid SDN/OSPF networking technique.

Hybrid SDN/OSPF represents a transitional networking architecture which allow the deployment of SDN in legacy networks, in an incremental manner, spanning several months or even years. The architecture is motivated by the manageable budgetary restrictions and technical constraints. In the perspective of MNOs and ISPs, hybrid SDN/OSPF provides a cost-effective option to deploy in the short-term. It requires very limited costs in terms of equipment replacement and the required expertise personnel. Besides, the hybrid technology requires limited technical expertise to make the minor modifications that are needed.

1) CHALLENGE

Over the years, the embrace of hybrid SDN/OSPF has steadily gained popularity among communication service providers, particularly MNOs and ISPs. Although this is a positive trend, it is not devoid of challenges. Existinghybrid SDN-enabled energy-efficient approaches are generic and reactive given their design nature. Besides, these approaches are characterized by manual control plane forwarding configurations. Consequently, such approaches cannot support the important requirement to optimise a trade-off between energy-efficiency and link performance [21], [22], with regard to all the important QoS metrics. This condition leads to network performance degradation. Essentially, the use of existing algorithmic approaches leads to sub-optimal network performance. Precisely, communications network vendors have a major uphill challenge to develop novel hybrid SDN/OSPF algorithmic approaches to ensure dynamic and flexible trade-off between the optimization of energy-efficient routing and performance with guaranteed QoS performance, without degrading network performance [23]. Principally, advanced networking architectures are needed to jointly support dynamic high capacity transmission requirements and green networking. Efforts should be focused on reducing network-driven operational expenditure (OPEX). The obtainment of such advance solutions can ensure the much desired end-to-end quality of transmission (QoT), by ultimately transforming service delivery, which is mainly characterised by better performance, flexibility and control.

To resolve the aforementioned challenge, it is essential for solution providers to devise advanced future-driven fine-grained network-based algorithmic approaches, that collectively consider the prioritization of all the important metrics in the operation of hybrid SDN/OSPF. Several years ago, various attempts have been made to resolve the challenge, but existing literature reveals that the advances in networking can quite be slow and inefficient [24]. We believe that in the current state of network evolution, a popular network design trend emphasizes a progressive transition from network-driven models based on QoS metrics to data-driven strategies. Precisely, these strategies consider the use of ML and DL techniques. The recent progress in ML and DL techniques such as convolutional neural network (CNN) and DRL, have proved past human level performance in addressing extensive online control tasks. Statistically, a majority of researchers believe that a popular solution to current challenges envisions and emphasizes combined embrace of the novel SDN architecture and learning-driven network analytics (NA), which precisely lays additional emphasis on the use of AI-enabled techniques in the control and management of networks [25]. Precisely, the recent promising combination of SDN, AI-assisted ML and DL techniques in traffic management and control provides a better tremendous opportunity.

During the last couple of years, ML has drawn immense attention from both industry and academia, owing to its superior performance in the viewpoint of extensive processing of data, classification of traffic flows, and smart decision making. For instance, a few recent seminal works have employed ML to address the concern of operational management and control in networks [26], [27].

Also, other studies have focused on the novel popular paradigm known as knowledge defined networking (KDN), that employ ML and cognitive approaches to ensure network operations [28]. This design can provide a substantial benefit to communications service providers and other actors, in the domain of networking, given the promising central concept.

Recently, it has become clear that SDN-based technology will advance to the next and much desired level of system intelligence, with specific focus on self-aware, self-adaptive, and reactive characteristic in regard to data analysis and AI in the future times. This advancement is envisioned to promote the use of approaches that enable the need to monitor, analyse, plan and execute (MAPE) policy actions. Obviously, it is imperative for emerging networks to address the need for more dynamic energy-efficient routing and QoS guarantees to improve network performance. Prioritising all the metrics is vital to the obtainment of an effective and perfect solution, which can otherwise lead to significant network performance degradation [29]. Specifically, the issue of energy-efficient routing with guaranteed QoS performance is an open research that deserves attention.

2) EXISTING SURVEYS OF SDN AND HYBRID SDN/OSPF

As summarized in Table 2, several extensive surveys on pure SDN such as [20], [34], [35] and hybrid SDN/OSPF networks such as [19], [37] can be found in the literature. Besides, a number of extensive surveys that focus on ML and DL in SDN-enabled networks have been published, for instance [24]–[27], [67]. Although the above surveys have considered a range of control studies in pure SDN and hybrid SDN/ OSPF networks, none of them has comprehensively considered such studies in the scope of ML and DL.

To-date, hybrid SDN/OSPF networking, and ML and DL problems have been researched independently. Generally, there are no reports on extensive crossover researches and algorithmic solutions between these two areas. Existing crossover researches have focused ML and DL in pure SDN. To our best knowledge, the subject domain of ML and DRL assisted hybrid SDN/OSPF networking has not been extensively surveyed to-date. With the current advances being witnessed in modern telecommunication networks, existing IP-based networks such as hybrid SDN/OSPF are envisaged to play a major role in the emerging networks such as 5G. Going forward, such IP-based networks need to be investigated to improve their potential in current and next generation communications networks.

C. MAIN CONTRIBUTIONS

Complementary to existing works, this paper addresses the following objectives. First, we provide a review of the most recent optimization approaches for global energy-efficient routing and load balancing. Next, we investigate a scalable and intelligent integrated architectural framework that leverages deep reinforcement learning (DRL) techniques to realize predictive and rate adaptive energy-efficient routing with QoS guaranteed performance, in transitional hybrid SDN/OSPF networks. Currently, there is a rapid rise in the cost of energy utilization in information and communication technology (ICT) sector, particularly MNOs and ISPs. This problem demands for mitigation approaches to respond to the new environment of hybrid SDN/OSPF. This paper provides key research insights into the current progress in hybrid SDN/OSPF, ML and AI in hopes of stimulating more research. We emphasize the viewpoint that intelligent hybrid DRL approaches will play an essential part in the realization of more progressive behavior in SDN-enabled networks.

1) ORGANIZATION OF THE WORK

The rest of the paper is organised as: Section II presents the background studies on traditional IP networks and hybrid SDN/OSPF. Section III presents an evaluation of recent studies in hybrid SDN/OSPF networks. Section IV presents the fundamentals of ML and DL the fundamentals of ML and DL algorithms. Section V presents the selected SDN-enabled ML and DL studies in the perspective of traffic prediction, routing, routing with QoS guarantees, energy-efficiency and hybrid or multifaceted cases. Section VI presents present the research challenges and future research direction. Section VII present the proposed ML and DL framework. Lastly, Section VIII provides the conclusion.

2) LIST OF ABBREVIATIONS

The commonly used abbreviations in this work are listed in Table 1. Observe that in this paper, we use the key words traditional and legacy interchangeably. Also, DRL is made up of two deferment algorithms namely Deep Q-Learning (DQL) and policy gradient [29], and for the rest of the paper, these two will be interchangeable used to make reference to DRL algorithm.

3) ROADMAP

Provided in Fig. 1 is a roadmap which points out the main aspects that are considered. The aspects are divided into two major parts that include, the reviewed work and the proposed framework. It attempts to provide a guide to ensure systematic flow, in order to promote the readability of the content.

II. BACKGROUND

The aforementioned section considered the introduction and motivation, meant to highlight to the readers the intension of

TABLE 1. Alphabetically ordered list of abbreviations.

ACRONYM	EXPLANATION	ACRONYM	EXPLANATION
5G	Fifth Generation	LapSVM	Laplacian Support Vector Machine
AdaBoost	Adaptive Boosting	LR	Linear Regression
AE	Auto Encoders	LSTM	Long Short-Term Memory
AI	Artificial Intelligence	MCSVM	Multi-Class Support Vector Machine
ARIMA	Auto-Regressive Integrated Moving Average	MILP	Mixed Integer Linear Programming
ARMA	Auto-Regressive Moving Average	ML	Machine Learning
BP	Back Propagation	MLP	Multilevel Perceptron
CDN	Content Distribution Network	MLU	Maximum Link Utilization
CFR-RL	Critical Flow Rerouting Reinforcement Learning	MOILP	Multi-Objective Integer Linear Programming
CNN	Convolutional Neural Network	NB	Naïve Bayes
ConvLSTM	Convolutional LSTM	NCA	Network Control Ability
CPU	Central Processing Unit	NN	Neural Network
CQM	Continuous QoS Monitoring	OSPF	Open Shortest Path Protocol
DCN	Data Centre Networks	PALR	Predictive Adaptive Link Rates
DDPG	Deep Deterministic Policy Gradient	PL	Polynomial Regression
DL	Deep Learning	PSO	Particle Swarm Optimization
DNN	Deep Neural Network	QoS	Quality of Service
DQL	Deep Queue Learning	RF	Random Forest
DRL	Deep Reinforcement Learning	RL	Reinforcement Learning
DT	Decision Tree	RNN	Recurrent Neural Network
E2E	End-to-End	RT	Random Tree
GA	Genetic Algorithm	RT	Regression Tree
G-AdaBoost	Gradient Adaptive Boosting	SA	Simulated Annealing
GNN	Graphical Neural Network	SAQR	Software-Defined QoS-Aware Routing
GPU	Graphical Processing Unit	SDN	Software-Defined Networking
HA	Heuristic Algorithm	SL	Supervised Learning
IP	Internet Protocol	SVM	Support Vector Machine
ISP	Internet Service Providers	TE	Traffic Engineering
KDN	Knowledge Defined Networking	USL	Unsupervised Learning

the paper. In this section, we consider background aspects in networking. Initially, the basics of TE in traditional networks is given. Subsequently, a brief account of hybrid SDN/OSPF is considered.

A. TE IN TRADITIONAL NETWORKS

This subsection provides a brief description of TE in traditional networks, that include IP-based network and MPLS-based networks.

Due to the explosive expansion of the networks and the rising volumes of traffic demands, the distribution of network traffic has increasingly become uneven. When traffic congestion occurs in a local network, it is likely that the rest of the network have light load. Today, the rapid advance of network hardware, high-speed switching and routing components and high capacity network links, communications service providers can upscale hardware resources in their networks, a condition which minimizes network congestion to some degree. But, the overprovisioning approach to bandwidth obtainment is achieves at the cost of network utilization and does not address the issue of network congestion in hot-spot communications channels.

TE is a valuable method concerned with study of how to quantity and analyze network traffic in real-time, and develop realistic routing apparatus to schedule and forward traffic flows, to enhance the utilization of the resources of the network, and improve QoS demands [20], [31]. The goal in TE is to balance traffic flows and optimize routing for traffic delivery, to make the most benefit with network resources. In traditional networks, the path is determined in the multipath scenario through cooperation between switches, a strategy which leads to the inability to understand the network topology and perception of the network state information.

Generally, two TE approaches have been developed to achieve TE requirements in traditional networks, namely IP-based TE and Multiprotocol Label Switching (MPLS). In a multipath scenario, the IP-based TE approach addresses the issue of load balancing by optimizing the IP routing algorithm to overcome network congestion. Moreover, in such networks all routers execute distributed protocols such as OSPF [32]. Thus, as suggested in [33], traffic is routed through the shortest path or least cost path, where network links are assigned individual link weights or costs. As such, a neighborhood search is done based on the attained OSPF link

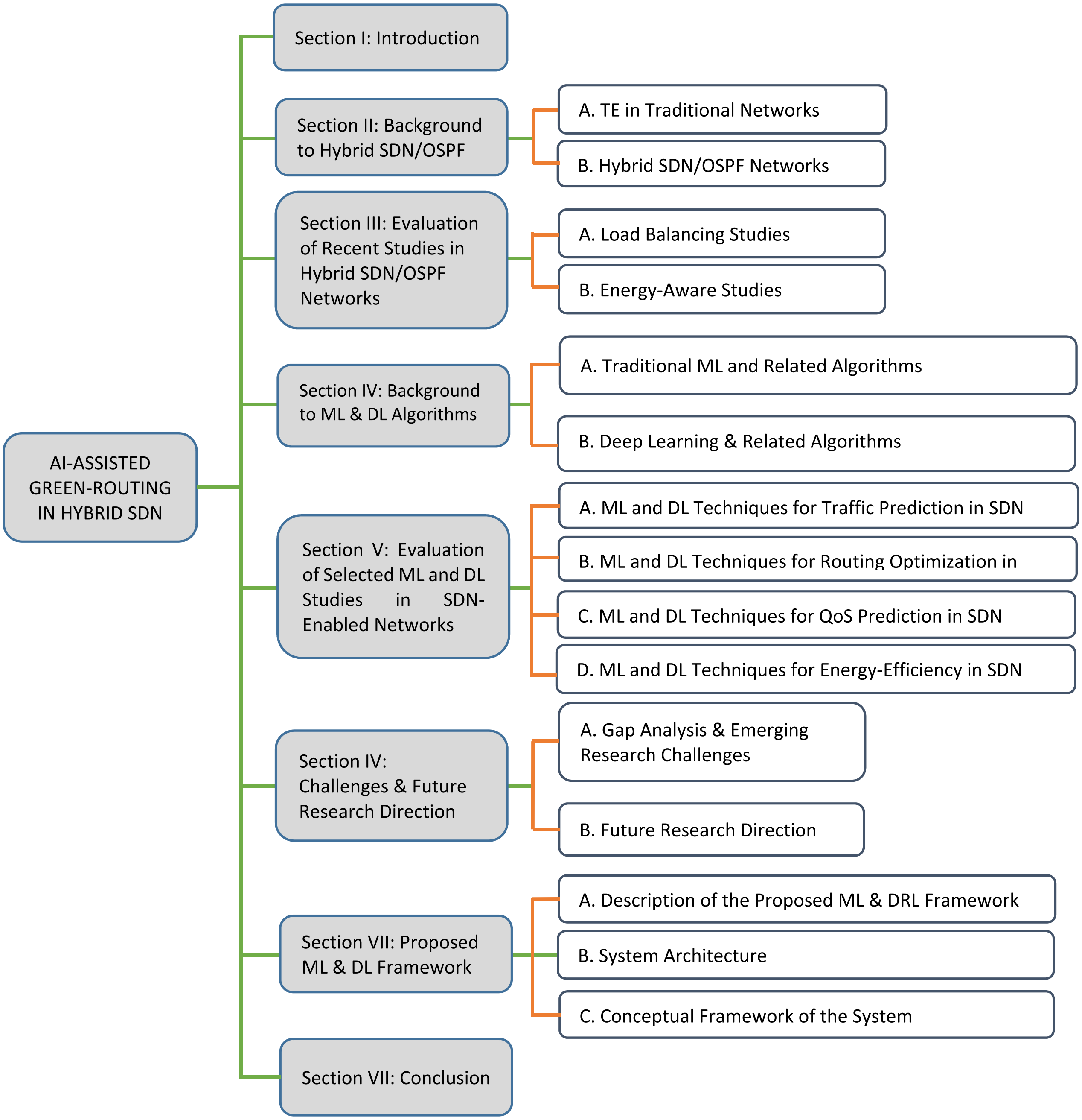

FIGURE 1. **A roadmap showing key aspects of the reviewed works and the proposed framework.**

weights to fine-tune the current routing computation strategy, hence generating the multiple equivalent shortest path between the same router pair to achieve traffic load balancing [34]. Although traditional IP networks employ IP headers to achieve load balancing and deliver good performance, they are unsuitable for dynamically changing network scenarios since they use the static shortest path routing algorithms, where mapping of flows to shortest paths does not reflect the current state of network utilization, flow size and topology changes [35].

In a dynamic network scenario, such a condition can overwhelmingly overload the routers or switch buffers, thus degrading the entire network performance. Also, static IP-based routing algorithms cannot provide adequate TE support in dynamic networks with a diversity of applications [20], owing to their lack of capacity to split traffic flows among the generated multiple paths. In IP-based networks, the dynamic network topology conditions with changing traffic volumes, typical of some current and future networks complicates the determination of accurate network traffic matrix estimates. This is because traditional IP routing techniques employs a single table which is inaccurate in the context of dynamic networks. So, the Multiprotocol Label Switching was proposed to forward data packets [36],

TABLE 2. Related top level articles and the scope of this survey in SDN-enabled networks.

Publication	A Single Sentence Summary	Scope			
		ML	DL	Pure SDN	hybrid SDN/ OSPF
Mendiola et al. (2014) [36]	A roadmap for traffic engineering in SDN OpenFlow networks	×	×	√	×
Vissichio et al. (2014) [40]	Opportunities & research challenges of hybrid SDN Networks	×	×	×	√
Shu et al. (2016) [20]	Traffic Engineering in SDN: Measurement and Management	×	×	√	×
Mendiola et al. (2017) [34]	Contributions of software-defined networking to TE	×	×	√	×
Fadlullah et al. (2017) [28]	Advancing ML for network traffic control systems	√	√	√	×
Sinha et al. (2017) [43]	Hybrid Software-Defined Networking	×	×	×	√
Amin et al. (2018) [19]	A comprehensive survey of hybrid SDN networks	×	×	×	√
Luong et al. (2019) [25]	Applications of DRL in communications and networking	√	√	√	×
Latah & Toker (2018) [67]	Artificial Intelligence Enabled Software-Defined Networking	√	√	√	×
Boutaba et al. (2018) [27]	ML for networking: Evolution, applications & research challenges	√	√	√	×
Xie et al. (2019) [66]	SDN-enabled ML Techniques	√	√	√	×
Zhao et al. (2019) [26]	Applying the SDN concept based on Machine Learning	√	√	√	×
Huang et al. (2019) [41]	Hybrid SDN deployment approaches and optimization strategies	×	×	×	√
Our Work	AI-Assisted Framework for Green-Routing and Load Balancing in hybrid SDN/OSPF	√	√	×	√

as opposed to the use of IP-based headers, but the scheme is extremely complex, potentially leading to high performance driven overheads. This makes it hard to meet the demands of network systems like data center networks (DCNs) that require much bandwidth, green energy savings and high reliability.

Precisely, given the increasingly enormous size, highly heterogeneous and complex nature of modern IP networks, the use of traditional IP approaches, such as OSPF for network configuration, optimization and troubleshooting are not efficient. Given the extensively distributed design nature, such legacy networks lack the capacity to ensure fine-grained network control management, and this imposes the condition to engineer novel networking architectures and related approaches to resolve the current problem. This is the exact context in which Software-Defined Networking architecture, particularly the transition hybrid SDN/ OSPF comes to the fore as a suitable alternative, to realize load balancing and overcome network congestion.

B. HYBRID SDN/OSPF

This section is dedicated to transitional hybrid SDN/OSPF networking architecture. Initially, hybrid SDN/OSPF is defined. Then, a brief description of the transitional hybrid SDN/OSPF is provided. Lastly, we provide the various hybrid SDN/OSPF designs.

1) HYBRID SDN/OSPF DEFINED

Hybrid SDN/OSPF refers to a networking design which enables various degrees of co-existence and communication between the centralized and decentralized designs, to ensure configuration, control, update and management of the behavior of the network, to optimize the performance of the network and user experience. In an effort to exemplify the levels of co-existence and communication, one can consider legacy switches that employ distributed protocols such as Interior Gateway Protocol (IGP), in order to exert overall control on the routing of network traffic flows, as opposed to SDN which routes traffic flows from a global perspective. By conjoining these two designs, and by assigning a portion of the traffic flows to be under the control of the traditional design, and by leaving the other portion to be under the control of the SDN-enabled controller, the hybrid SDN/OSPF network formation is realized. Fig. 2 is a generic representation of hybrid SDN/OSPF networking architecture.

Principally, hybrid SDN/OSPF networks consist of single path and multi-path scenarios. Moreover, as illustrated in the Fig. 2, legacy devices in such networks are beyond the scope of control of the SDN controller. Barely, one deterministic next hop calculated by the routing protocol can be used to transmit data. But, by leveraging the functionality of SDN, SDN-enabled nodes can assign traffic flows to multiple next hops. Lastly, hybrid SDN/OSPF network design contains controllable network path, basically a path which is controllable and deployed by a SDN controller. As given in the figure, communication between the SDN controller and the forwarding plane is done through the south bound interface (SBI). Also, the communication between the SDN controller and the application plane is done through the north bound interface (NBI). As previously stated, hybrid SDN/OSPF is a preferred alternative to pure SDN, the main reasons being the manageable budget constraints and limited technical restrictions.

2) DESCRIPTION OF HYBRID SDN/ OSPF

Following the above definition, one observes that hybrid SDN/OSPF provides a superior nonetheless significant network design advance, within which both forwarding legacy

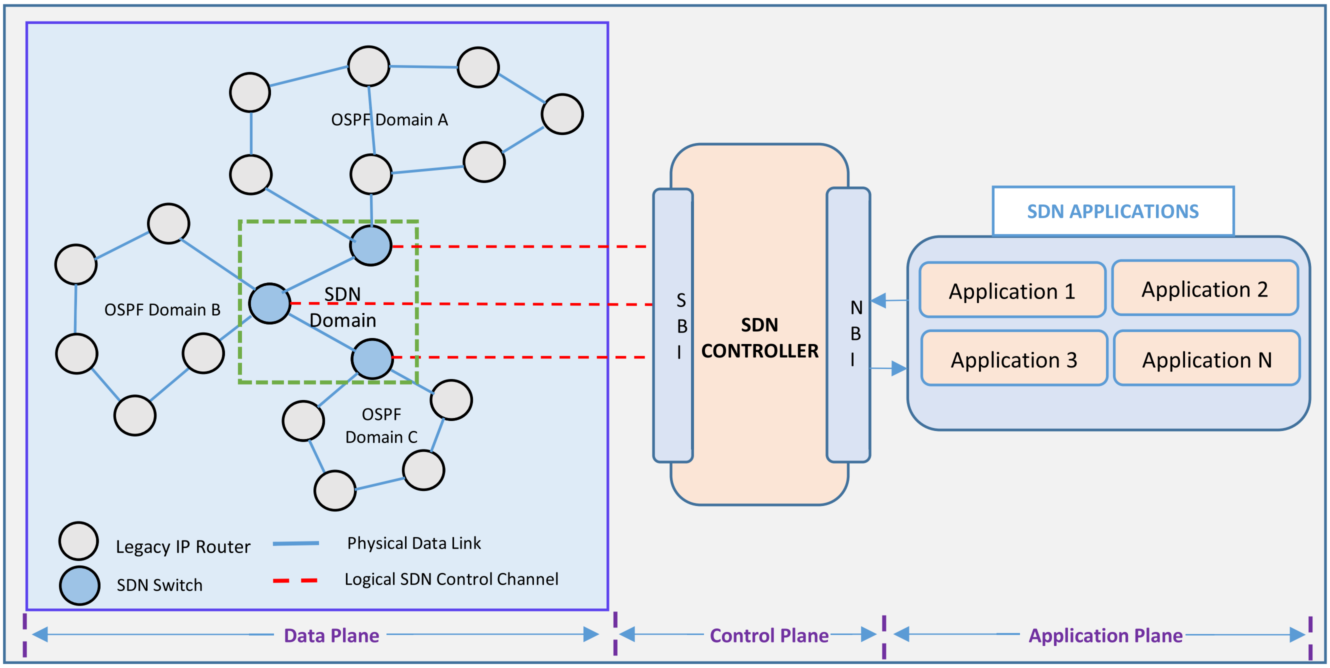

FIGURE 2. Hybrid SDN/OSPF setup: using SDN to partition legacy OSPF network.

devices and SDN-based devices are accommodated. As illustrated in Fig. 2, to ensure the exchange of information between these two categories of devices, SDN-enabled devices should be legacy-enabled to support the forwarding of link-state advertisements (LSA) [37]. This kind of configuration allows legacy devices to detect links to SDN-enabled devices. Also, it allows SDN-enabled devices to discover the links to legacy devices. This ultimately ensures the relay of information to the centralized SDN controller. Assuming legacy network implements hop-by-hop routing, based on a typical routing protocol such as OSPF, link state information can be captured using SDN-based devices and stored in the OSPF link state database (LSTB). Moreover, through the use of Link Layer Discovery Protocol (LLDP), Broadcast Domain Protocol (BDDP) and link information from legacy routing protocol like LSAs, the centralized SDN controller holds the capacity to generate enough network information, which include the network topology and link metrics. For more details on this, the authors in [38] have provided an in-depth coverage of network topology discovery process in such hybrid SDN/OSPF.

3) CLASSIFICATION OF HYBRID SDN/OSPF

There are different designs of hybrid SDN/ OSPF. Provided below is the classification of various hybrid SDN/OSPF based on design and components.

a: CONTROLLER ONLY [39]

This hybrid SDN/OSPF design involves the institution of a centralized SDN controller in the network, while the rest of the network is kept the same, making it essentially cost-free. The rationale is to improve the dispersed control plane with inputs emanating from the centrally located control which provides benefits such as global network visibility, quick convergence and traffic flow abstraction, among others. In terms of use, the controller only design allows the institution of a central control and the gradual transfer of control to the SDN controller with gradual technology maturity and acquisition of experts and the operators.

b: SDN AND NON-SDN ISLAND [19], [39]–[41]

This is a crossbreed design, constructed from both the control plane and data plane. The alternative name is Topology-based hybrid SDN/OSPF, given the topological separation of the nodes which are put under the respective control of each design. To illustrate its use, an enterprise can take a decision to upgrade a small part of its network to SDN-enabled, yet other parts remain intact, thus forming islands. The network is partitioned into SDN and non-SDN regions. In the SDN region, the control is centralized at the SDN controller, whereas in the non-SDN region, it follows a distributed arrangement. The communication between the two regions is based on a gateway device. The design is suitable for a migration plan where SDN is embraced based on regions. The motivation underlying the design is related to the need to initiate migration based on a limited region, self-confidence development and know-how and the then move to the subsequent stage. The investment cost depends on the number of SDN-enabled nodes deployed in the target SDN island.

c: EDGE PLACEMENT [39]–[41]

This design is proposed to suit the delivery additional intelligence routing within the boundary of the network, as opposed to the centralized hub and spoke design, while ensuring optimization of traffic flows and security or QoS guarantees without raising costs. The design is based on the view that future networks will trend towards edge-based network intelligence. This can potentially simplify the management and control of networks, due to separation of the control and forwarding operations, allowing different challenges to be resolved.

To implement this design, SDN-enabled nodes are deployed at the network edge, in which case the centralized SDN controller exerts control on the forwarding decision at the network edge positioned nodes. As per the controller, the topology is purely restricted to the SDN-enabled nodes. The core network traffic flows depend on the legacy protocols. Moreover, the SDN design is charged with the management of network traffic exchanges beyond the network boundary, such as the Internet. One benefit of separating the network edge from the core network regard the requirement to successfully map the destination IP addresses of the inward packets to the unused IP addressed to support customizes routing over legacy network.

By deploying edge-based SDN-enabled nodes, the approach can dedicate the much desired SDN intelligence at the network edge. This strategy provides a strong motivation for SDN migration journey. However, the level of investment is commensurate to the number of SDN-enabled devices deployed and this can be costly. Generally, this approach allows the maximization of network performance, while minimizing both CAPEX and OPEX.

d: WITH MIDDLEWAR [19], [39]–[41]

Principally, this design is intended to address the requirement to exert SDN-like control on the existing data-plane at reduced cost. The motivation of the design involves the need to extend SDN-controller capacity to comprehend legacy protocol using a software component called middleware, which facilitates the exchanges between the SDN controller and legacy devices. To achieve the above requirement, the SDN controller employs a legacy network protocol (middleware) to communicate and change the configuration setting of existing legacy devices, yet maintain control over SDN switches in the normal way.

To implement this design, a two-stage migration plan ought to be embraced. As an illustration, following the maiden transition phase from legacy to controller only design, moreover having obtained the required confidence and know-how, the second step involve progressive change of the data plane by adding SDN-enabled devices, and hence progression to complete deployment of SDN. Recall that achieving this end involves a gradual investment approach.

e: WITH UPGRADE/AGENT [39]–[41]

This design focuses on delivering SDN-sort of control. Basically, it represents the need to twist legacy devices to allow communication with the SDN controller, through software upgrades, precisely agents. The design strategy helps to promote cooperation and improve the comprehension ability of SDN protocol, to ultimately improve communication with the SDN controller using SDN agent. The cooperation between the distributed and the centralized routing control plane can be based on hardware such as hybrid switches or software components which are introduced in the legacy networks. The approach demands for mere deployment of only the SDN controller in the existing network. The approach is beneficial in that it promotes least utilization of current hardware and can hence minimize the levels of investment.

f: SDN OVERLA [39]–[41]

This design enables the construction of an SDN overlay above legacy networks. The design is motivated by the requirement to maximize the benefits of SDN. Moreover, the level of investment is dependent on the design and application of the overlay. During the transition progression, the design suffers protracted interruption of services, since it requires network reconstruction. The overlay network is configured to ensure complete support of network programmability and policy execution and upgrade, though un-observed traffic flows in the underlay network may not provide full support to this. Moreover, scalability function is attributed to network design and the logically centralized controller load. Finally, the recovery function provided by both the SDN controller and the legacy network protocols.

g: THE SPINNING CONTROL THEORY

Although the previous subsection has considered the various designs of hybrid SDN/OSPF, this work is based on the pinning control Theory [42] as the reference theory this work. The pinning control theory, is an emerging network control theory designed to guide the management and control of complex networks based on partial control of nodes. In practice, the theory enables by selection and configuration of a subset of network nodes, to exert a wider or even global network control. The selected subset of network nodes is deployable to manipulate the routing of traffic in a large-size network scenario. Recently, the pinning control theory has attracted the interest of many networking researchers, in the control of complex networks amidst the rising levels of dynamic traffic demands and the need to ensure reductions in CAPEX and OPEX, in the perspective of the telecommunications industry.

h: CHOICE OF NETWORK ARCHITECTURE

Based on the proposed pinning control theory, this work intends to leverage the functionality of SDN, by using SDN-enabled nodes to assign traffic flows to multiple next hops. Primarily, there are two main designs under consideration. First, we consider *SDN and Non-SDN Islands* design, where hybrid SDN switches are deployed in legacy network, among legacy IP switches to form a hybrid SDN/OSPF network. Second, we consider using *with upgrade/agent* design. Moreover, the cooperation amidst the distributed and the centralized routing control plane can be based on hardware such as hybrid switches or software components which are introduced in the existing legacy networks. By building a hybrid

SDN/OSPF network, old legacy switches can be employed to achieve SDN-like network control and operations management in legacy network regions.

III. EVALUATION OF RECENT STUDIES IN HYBRID SDN/OSPF NETWORKS

In the previous section, the focus was on the introductory aspects in this work, including basic coverage of SDN and hybrid SDN/OSPF networking. Building on that foundation, this section provides a detailed coverage of the selected and reviewed load balancing and energy-aware routing research works in the recent past in hybrid SDN/OSPF networks. These works have been carefully selected and tailored towards meeting the problematic requirement for much desired network intelligence and automation, in the existing and future SDN-enabled energy-aware high speed communication networks. Clearly, some of the works investigated have not been reviewed in existing works, indicating that they are current works.

A. LOAD BALANCING STUDIES

This section provides a review of a few most recently selected load balancing research works in in hybrid SDN/OSPF.

In communication networks, load balancing Load balancing represents a major traffic engineering (TE) method whose purpose is to improve the delivery of data traffic loads over various resources driven by a particular performance measure [31], [34], [43], [45], [46]. With regard to hybrid SDN/OSPF, the TE goal of attaining maximum link utilization (MLU) can be made achievable using data traffic flow load balancing to ensure a congestion free network. Because the purpose of load balancing involves the determination of average link rate utilization for the entire network links, telecom carriers are able to reduce OPEX, hence supporting extra network users [24], [47]. This can ultimately indicate enhancements in network performance using throughput, packet loss, link failure and delay and jitter. Owing to the recent growth in network data traffic flows and industry uncertainties, for instance capital expenditure (CAPEX) and operational expenditure (OPEX), energy efficiency, QoS services or application guarantees and load balancing challenge, particularly in multipath network environment, have all become very important issues in SDN-enabled networks [48].

Guo *et al.*, [49] considered the challenge of inefficient traffic flow routing and scheduling in order to alleviate network congestion and improve load balancing. They devised an innovative routing and flow scheduling mechanisms which uses the SOTE algorithmic framework, to achieve path reduction, and ultimately enhance network performance. The mechanism so proposed was meant to jointly configure the OSPF weight setting and network traffic flow splitting fraction to minimizes the MLU in the perspective of ISP networks, through the migration progression. They employed SDN-based controller to optimize OSPF weight setting particularly by way of splitting the inward traffic flows at the SDN nodes, to reduce the MLU. Besides, the legacy networks execute OSPF given their normal operation. The proposed mechanism can improve network performance by ensuring resilience to path failure, owing to the re-routing technique that it employs. Moreover, acceptable levels of performance can be achieved using a small number of SDN-enables switches. However, the mechanism has various challenges: only OSPF congestion problem is considered; more CPU time is required to compute path reduction; suffers the occurrence of network loops and black holes, thus resulting in network performance degradation.

Caria *et al.*, [50] suggested an idea to partition a given OSPF domain to attain SDN-enabled TE. The plan was to exploit SDN-enabled edge routers to improve control over the various routes that interlink the sub-domains. Specifically, in TE perspective, the interest was to deal with routing inefficiency to ensure load balancing by improving link state updates. A unique routing mechanism was proposed where the whole network is partitioned into multiple sub-domains interlinked using SDN-enabled edge positioned devices. The solution includes a TE engine which employs ILP based algorithm to attain traffic load balancing goal. The performance of the mechanism depends on the number of sub-domain partitions within the entire network. The mechanism exhibits low overheads with improved resilience to failure. Besides, it provides additional flexibility because it goes beyond minimizing link utilization. One limitation faced Is that the locally placed internal domain routers cannot be put under the SDN controller, thus they truck the OSPF network protocol and route on the shortest paths. Lastly, it is static since the ILP assumes that each OSPF path within the sub-domain is known and constant.

Chu *et al.* [51] conducted an investigation on the issue of traffic flow reachability and recovery in a scenario of single link failure. Moreover, the actors contextualized a situation where one of the links fails, in which case the proposed legacy IP router has to handle the forwarding of the target packet to a specific SDN switch by bypassing the link under failure. When traffic network flow is redirected from the failed link to the target SDN-enabled switches, based on pre-computed IP tunnel, the existing network can rapidly respond to failures. Based on the synchronized capability exhibited among SDN-enabled switches, coupled with the universal view of the controller, the system can devise additional backup paths in order to assure network traffic flow recovery with load balancing improvements. This can help to resolve the problem of network congestion, to enhance load balancing in regard to post network recovery efforts. However, the procedure intensifies the precomputed control burden, thus wasting the flow table entries.

Hu and Wang [52] considered the issue of routing in TE, purposely to maximize controllable traffic. They proposed a mechanism that employs a fully polynomial approximation scheme (FPAS). Moreover, one traffic class was considered, with the purpose to maximize network traffic flow, through leverage of the barrier and hybrid network deployment modes. The performance was compared against that of

OSPF routing scheme. The emphasis was on source redirection gain for the TE problem, based on MLU. The hybrid SDN/ OSPF network was observed to outperform legacy networks. Although it is efficient in small networks, application in dense networks is very challenging, leading to a significant compromise in network routing efficiency. Besides, the solution is suitable for single domain ISP content distribution networks (CDN), making it inefficient in multi-domain scenario. Also, it disregards the important consideration of energy-saving requirements in TE. Lastly, only MLU, latency and fault tolerance are considered, which limit the capacity to guarantee QoS-based service provisioning.

He and Song [53] considered the issue of routing and traffic scheduling in TE. They suggested a TE routing and traffic flow scheduling centered on barrier mode in an overlay network setting. In terms of performance, the proposed mechanism was compared against that of OSPF routing system, with particular focus on source redirection as respect to the TE problem, by using MLU metric. Precisely, it was noted that distributing SDN traffic between various sources can substantially enhance performance without creating overheads. But, source request redirection is not dynamic and lacks the efficiency to distribute traffic flows and ensure link utilization. Also, the mechanism only considers MLU and cannot support priority-based QoS classification of traffic, which degrade network performance. Overall, the mechanism in can achieve a high link utilization compared to that in [49]. This condition is especially so with a dynamic number of SDN traffic flows, because it eliminates network congestion. Moreover, the proposed destination-based routing leads to high levels of latencies, with limited tolerance to path failure, since there are no alternative routes for traffic flows. Nonetheless, the mechanism in [49] is tolerant to path failure, given its efficient re-routing method.

Ren *et al.*, [54] studied network traffic routing and scheduling in TE with the purpose of enhancing network traffic flow management. The authors proposed a routing and traffic flow splitting mechanism to achieve efficient management of routes, by mainly optimizing the MLU and traffic flow splitting fraction. The proposed mechanism is limited due to routing efficiency degradation mainly brought about by the longer path generated, when compared with other routing mechanisms the operate without traffic flow splitting. Moreover, the mechanism only considers MLU, latency and fault tolerance, in which case it can potentially lead to performance degradation. Also, the internal sub-domain routing is beyond the control of the centralized SDN controller, in which case such control still falls under the province of the OSPF protocol, which routes through the shortest path. Overall, the proposed mechanism exhibits better performance as opposed to related state-of-the-art works such as the one which is employed in [51], wherein the OSPF domain is partitioned into sub-domains using SDN switches.

Lin *et al.*, [55] considered the issue of QoS-based routing in such hybrid networks. They suggested a network design which uses QoS-aware routing (SAQR) method, that employs simulated annealing (SA) to update the weights for delay, traffic loss and bandwidth demands, in a dynamic manner. Besides, the approach uses the spanning tree algorithm to achieve discovery of legacy switches in such hybrid networks. Moreover, suitable dynamic paths are defined to route the data traffic over paths that meet the desired QoS routing demands for multiple applications, taking into account the current network state. Besides, it employs the Learning Bridge Protocol (LBP) to ensure coordination between legacy and SDN devices. This removes the need to modify legacy devices which is a requirement under ordinary circumstances. Precisely, the protocol is based on link layer (L2) routers and switches, although an extension to network layers (L3) routers and switches is possible. The mechanism exhibits better performance in terms of bandwidth, delay and loss rate with improvements in the volume of network traffic flows that achieve corresponding QoS demands.

Bi *et al.* [56] addressed the problem of intelligent QoS-driven forwarding of traffic in hybrid SDN/OSPF industrial Internet, precisely to support existing and emerging industrial manufacturing. Based on recent observation, industrial Internet has gained much attention from researchers in both industry and academia. It was also observed that traditional industrial networks can barely meet the QoS needs of certain mission-critical industrial applications or services. Accordingly, they proposed smart-QoS-guaranteed forwarding mechanism to enhance the QoS in these applications. In the work, they employ a minimum cost single-path forwarding approach and k-path algorithmic framework to ensure multipath forwarding.

This subsection has focused on the different routing mechanisms with traffic load balancing in hybrid SDN/OSPF networking, a summary of which is provided in Table 3 and 4.

B. ENERGY-AWARE ROUTING STUDIES

While the previous subsection has discussed the various selected studies on load balancing in hybrid SDN/OSPF, this subsection focuses on the various energy-aware routing approaches, with and without load balancing in such hybrid networks.

In legacy networks [57], [58], the growing energy utilization of networking elements result in challenges such as rising levels carbon dioxide (CO_2) emission and cost of network operations. Specifically, a large portion this utilization is due the core and backbone networks, especially IP routers, while a minimal share is owed to the carried network traffic load. Realistically, communication networks are devised to support the distribution of traffic demands during peak time, however during off-peak times the volumes of carried traffic fall below the defined network capacity.

Precisely, it is the above context that researchers have been driven to proposed innovative energy-efficient approaches and mechanisms to minimizes the number of active network links, necessary to assure traffic flow routing and forwarding without experiencing link overload. Although past researches have attempted to put emphasis on the issue of performance

TABLE 3. A comparative summary of different routing mechanisms with traffic load balancing.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Guo et al. (2014) [49]	Objective: To address the problem of routing and scheduling during weight setting for flows and TE in OSPF-SDN networks. Mechanism: proposed a re-routing strategy to optimize OSPF weight setting to minimize link utilization and CPU time. Metric: Maximum Link Utilization and CPU time Emulation/Simulation Tool: Rocket Fuel Technologies and Custom Development Environment: Fixed Network	• The study only considers the problem of network congestion.
Caria et al. (2015) [50]	Objective: Addressed the need to partition OSPF network into sub-domains to realize SDN-based TE by enhancing control over the interconnecting sub-domain routes. Mechanism: Devised a strategy of partitioning the entire OSPF network is into sub-domains, moreover interlinked only by SDN-enabled devices strategically located at the edges, to achieve route control over traffic between sub-domains. Metric: Throughput was used to measure the extent of data loss. Emulation/Simulation Tool: SNDlib Library Environment: Fixed Network	• The solution is static and hence inefficient and not applicable in dynamic network scenarios. It assumes that all the internal OSPF paths are already known and are constant • Only considers throughput to measure the level of data loss, without using QoS guarantees based on traffic classification which can lead to performance degradation
Chu et al. (2015) [51]	Objective: Addressed the problem of reachability and fault tolerance in hybrid SDN networks Mechanism: Devised a fast response failure recovery strategy based on tunneling to assure reachability Metric: Maximum Link Utilization Emulation/Simulation Tool: Numerical Analysis, Custom Simulator. Environment: Fixed Network	• The procedure intensifies the pre-computed control burden or overhead, hence wasting the flow table entries. • Does not consider the objective of energy saving in TE. • Can lead to network congestion.
Hu et al. (2015) [52]	Objective: Addressed the issue of routing inefficiency in TE by maximizing the network traffic flow through the deployed SDN switches Mechanism: Suggested a routing mechanism that tunes SDN switch behavior in terms of flow forwarding to enhance the capability of legacy devices. Metric: Maximum Link Utilization. Network Topology: Simulation based on mathematical formulation. Environment: Data Center Networks	• Efficient in small-sized network as opposed to scaling large-sized multi-domain networks, with more dynamic traffic flows, leading to a significant fall in the routing efficiency of the network • Does not consider the importance of energy saving requirement in TE • Only considers maximum link utilization, latency and fault-tolerance. However, it cannot assure priority-based QoS guarantees, a thing which can degrade network performance
He & Song (2015) [53]	Objective: Addresses the TE optimization issue of routing and scheduling in hybrid SDN/OSPF networks. Mechanism: Suggested a routing and scheduling strategy which combines the capacity of legacy networks and control capability of SDN to attain efficient traffic delivery and link utilization. Metric: Maximum Link Utilization and TE flexibility Emulation/Simulation Tool: Theoretical/ Numerical Analysis, Custom Simulator. Environment: Fixed Network	• Source request redirection decision is still static and hence inefficient with regard to traffic flow request distribution and link utilization • The mechanism only considers maximum link utilization and cannot ensure priority based QoS prioritization which can impair network performance

TABLE 4. Continued from TABLE 3.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Ren et al. (2016) [54]	Objective: Addressed the routing problem of congestion in TE by improved management of flow routing and splitting Mechanism: Suggested a TE flow management mechanism which make it compulsory for every flow to path through an SDN-based switch to enhance flow control and TE Metric: Maximum Link Utilization and Latency. Emulation/Simulation Tool: FRS and Custom Development. Environment: Fixed network	• Degrades routing efficiency since flow splitting and aggregation without priority based QoS guarantees leads to lengthier path, resulting in latency and jitter • Only considers maximum link utilization, latency and fault tolerance and cannot ensure priority-based QoS guarantees, leading to performance degradation
Lin et al. (2017) [55]	Objective: Addresses the problem of QoS routing in hybrid SDN data center networks. Mechanism: Suggested a QoS-aware routing mechanism built on SA technique for a multi-service multi- constraints network scenario. Protocol: Proposed a simulated annealing QoS routing (SAQR) and adaptive weight setting algorithmic framework Metric: Packet loss, Delay and bandwidth utilization Emulation/Simulation Tool: Floodlight and Mininet. Environment: Data Center Networks	• The procedure is inefficient because its computationally complex and can lead to high processing delays, that can impair network performance • Does not take into consideration the mitigation of the impact of network related disturbances and service disruption due to flow rerouting • The mechanism lacks the resilience to overcome path failure because it does not employ the use of backup path
Bi et al. (2020) [56]	Objective: Addresses the problem of QoS routing in hybrid SDN Industrial Internet. Mechanism: Suggested a smart QoS-guaranteed multipath traffic forwarding mechanism to support critical industrial application delivery Protocol: Proposed a single-path least cost multipath forwarding and k-path algorithmic framework Metric: Packet loss, latency and bandwidth utilization Emulation/Simulation Tool: Theoretical/ Numerical Analysis Environment: Industrial Internet	

and cost of ICT, there is an urgent call for networking research community to devise working solutions to energy-efficiency problem. The need to resolve these requirements necessitate the design of energy-efficient network optimization, alternatively termed green network design criteria [58]–[61].

Wang *et al.*, [62] studied the need to minimize excessive energy utilization in communication networks. The authors suggested a dynamic spanning tree grouping scheme with the aim to determine network sub-sets with minimal energy consumption, to consequently put-off unused network elements and links to deliver the varying traffic loads. But, because of the static nature of the scheme, energy saving can only be realized when network loads are low, such as night-time. This condition can be a significant limitation to energy-efficient routing in practical networks. It is observed that only SDN nodes and the connected links can get into sleep state, while legacy devices are kept fully active. Also, computational overheads arise especially, during high peak periods leading to link overloads, causing undesired delays and packet loss. Additionally, the solution only considers MLU, throughput and power saving gain, while disregarding QoS prioritization of different traffic classes leading to link performance degradation.

Wei *et al.*, [63] investigated the problem energy-efficient routing and traffic scheduling in the backbone domain of hybrid SDN/OSPF network. Subsequently, they proposed a heuristic-based energy aware traffic engineering (HEATE) scheme for such hybrid networks. Their objective was to achieve minimal network energy utilization by computing the optimal link weight setting of legacy OSPF, including the splitting fraction of SDN switches. The scheme was revealed to perform joint optimization of OSPF link weight setting of legacy IP routers and flow splitting fraction of SDN-enabled switches. This enables the aggregation of controllable and uncontrollable traffic flows on partial links, thus turning off underutilized links to ensure energy conservation. The solution performs well in terms of energy-savings when energy-aware OSPF is combined with energy-aware forwarding algorithm (EA-FA). But, the mechanism lacks the desired dynamicity and efficiency to allow execution in the backbone network. Also, it not possible to achieve a balanced trade-off between energy-saving and TE performance, a condition which degrades network performance. Lastly, the solution only considers MLU which is a major performance limitation.

Recently, Huin *et al.*, [64] conducted a study on routing in TE in order to resolve the issue of energy consumption in hybrid SDN/OSPF networks. They proposed a two-stage energy-aware routing mechanism to turn unutilized network links to sleep mode to reduce energy use in such hybrid networks. However, a major challenge of the scheme is the need to ensure a high level of QoS guarantees when certain network components are in sleep mode. Specifically, the mechanism cannot provide the desired levels of link performance as per the defined indicators, much as this condition is critical in the correct operation of hybrid SDN/OSPF networks. Additionally, the proposed solution is limited since only SDN elements and the related links are made to sleep, whereas legacy IP devices are kept fully active. The routing solution can potentially be extended to prioritize QoS provisioning to ensure effective solutions, mainly by determining the best balance between quality and challenges that are related to the environment.

Jia *et al.*, [65] conducted a study on segmented traffic flow routing and scheduling in hybrid SDN/OSPF. They examined the challenge of path control and energy-efficient routing in the context of incrementally deployed hybrid SDN/OSPF, in ISPs and data center networks (DCNs). A more viable explicit path control (EPC) solution that is based on segment routing and scheduling was proposed. The solution can significantly improve network performance through flow re-route in small networks. But, it is not efficiency in multi-domain networks with large traffic volumes and dynamic traffic flow demand patterns. Although the scheme considers various QoS metrics such as MLU, throughput and power gain, this is done more generically and so cannot prioritizing traffic flows, a condition which can degrade network performance.

Finally, Maaloul *et al.*, [66] considered energy saving problem in the case of carrier-grade Ethernet network. In their work, the authors suggested a traffic-aware routing and load balancing scheme to shut down the minimum set of network elements and links, so as to achieve energy-saving and QoS guarantees free of network performance degrading. The mechanism so proposed takes into consideration rules space capacity restriction of SDN switches, conservation of network traffic flow and restrictions on resource usage. With regard to performance, the proposed scheme is capable optimizing the trade-off between energy-efficiency, network resource use and performance. The solution can also be able to ensure near-optimal performance within a much reduced time frame. But, the adjustment of the proposed solution to support the processing of port status and line rates can result into overheads in the scope of the control plane and increase transmission delay amidst the SDN controller and the forwarding plane.

Summary: As summarized in Table 5, green computing and networking has become a very important area of research in recent years. To date, many load balancing schemes have been suggested with the aim of ensuring energy-efficiency in SDN-enabled networks, but many challenges still exist, and these call for comprehensive approaches to be resolved.

IV. OVERVIEW OF ARTIFICIAL INTELLIGENCE TECHNIQUES

This section reviews the fundamental aspects of artificial aspects of artificial intelligence (AI), paving the way for an in-depth discussion of pertinent techniques in the field.

AI represents a rapidly growing field of science and engineering which features the use of methods that empower or endow computing devices (machines) and systems with advanced capabilities to imitate human behaviour [68]. Besides, AI is considered as an increasingly growing computation paradigm, whose objective focuses on teaching computing devices how to work and respond in a human-like manner. Moreover, such computing devices are endowed with advanced capabilities that include natural language processing, knowledge representation, automated reasoning, machine learning and computer vision. For a long time, AI has been employed in the optimization of communication networks with diverse requirements. Based on the above capabilities, diverse AI techniques fall under the broad field of machine learning (ML), expert systems and evolutionary algorithm. In relation to these, ML allows artificial procedures to capture knowledge from available raw and execute decisions without need for explicit programming.

A. MACHINE LEARNING

ML refers to data-driven analytical techniques that are capable of being trained to learn from data and make decisions. In terms of tools, ML technique employs computer programs which are trained on the collected data as opposed to preprogramed instructions. One should observer that ML concepts are simple and are concerned with a simulative reflection "induce" and "predict" employed in practical learning and growth process in humans. Generally, the concept of ML approach is built on induction and synthesis, as opposed to deduction.

Much as ML is an old technology, its use has not been widespread until recently when it re-emerged as an intelligent approach that promises to transform the domain of

TABLE 5. A comparative summary of different energy-aware routing approaches with and without load balancing.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Wang et al. (2016) [62]	Objective: To address the issue of high power consumption using a Heuristic Algorithm and OSPF Mechanism: Mechanism to ensure efficient link utilization based on the use of minimum power network subsets. Metrics: MLU Emulation/ Simulation Tool: Mininet Environment: Fixed Networks	• Not dynamic since it can only save energy at night when network traffic loads are low • Does not consider the TE objective of load balancing • Only considers maximum link utilization, throughput and power gain and cannot not priorities QoS guarantees by traffic classification which can degrade network performance
Wei et al. (2016) [63]	Objective: Routing and scheduling based on flow splitting to ensure energy-efficiency in the backbone networks scenario. Mechanism: To determine the optimal link weight setting and flow splitting fraction for OSPF, and aggregating flows on partial links, thus putting off underutilized links to save energy. Metric: Maximum Link Utilization Emulation/ Simulation Tool: Mininet Environment: Fixed Networks	• Static and inefficient hence limiting its execution in the backbone network, and this can lead to sub-optimal performance • Cannot ensure a balances trade-off between energy-saving and TE improvement which can lead to performance degradation • It only considers maximum link utilization and power gain and does not priorities QoS guarantees based on traffic classification which can lead to performance degradation
Huin et al. (2017) [64]	Objective: Routing and traffic load rate adaptation in TE to address the high energy utilization problem using OSPF and OpenFlow. Mechanism: Mechanism that adapts routing to traffic load to spare and turn off unused network devices and links into a sleep state to minimize energy consumption, while ensuring failure tolerance. Metric: Throughput was used to measure the extent of data loss. Emulation/ Simulation Tool: Mininet Testbed with SENAtoR Environment: DCNs	• Inefficient because it is computationally complex to implement • Ensures high levels of QoS guarantees when certain number of network devices are in their sleep state
Jia et al. (2018) [65]	Objective: To examine and address the problem of path control with energy saving in hybrid SDN/ ISP and DCNs with incremental switch deployment using OSPF Mechanism: Devised a two-stage strategy to turn-off redundant networked switches and links while leveraging segment routing between SDN switches to guarantee energy saving. Metric: Network Control Ability (NCA) and Power saving gain Emulation/ Simulation Tool: Rocket Fuel Topologies and Custom Development. Environment: DCNs	• Efficient in small-sized networks as opposed to multi-domain networks with large traffic volumes and dynamic traffic flow demand patterns • Only considers maximum link utilization, throughput and power-gain, and cannot priorities QoS guarantees based on traffic classification, which leads to network performance degradation
Maaloul et al. (2018) [66]	Objective: To addressed the problem of energy saving with QoS guarantees in ISP networks Mechanism: Proposed traffic-aware routing mechanism to ensure trade-off between energy saving and performance by shutting down unused network subset Metric: Traffic Load, Fairness of Traffic distribution, Network Connectivity, Average path length Emulation/ Simulation Tool: Custom Development Environment: Fixed Network	• Inefficient due to the high signalling overheads and hence increased communication delays between the controller and the data plane forwarding devices. Subsequently, the lengthy execution delays incurred can limit the request response time of the network

event classification and prediction. Owing to the advances in ICT in the last decades, the increasing expansion and complexity on networks and huge growth in data rates have driven researchers to advance and embrace the intelligent power of ML and DL to perform network management and control, let alone harness the growth in data volumes. The progress in ML and DL techniques are envisioned to perform a significant part in current and future networks. For a comprehensive review of ML algorithms used in SDN traffic classification, optimization or routing and QoS and QoE prediction, see [67], [68].

Historically as hinted above, ML was a less popular area, however with the advances in computational power, graphical processing units (GPUs) and the increasing availability of data, machine learning field has advanced by leads and bounds. These advances have motivated modern research to unleash the substance of huge data by state-of-the-art technologies. Principally, the ML approach entail implementation phases that include pre-processing, training and testing. Included under pre-processing are actions like data pre-processing, sifting, imputation, in addition to tuning for specific purposes. After processing the data, ML learning techniques are applied to perform data training. Then, the system makes decisions based on the input and out of the training phase.

Machine Learning and Related Algorithms: This subsection considers the basics of traditional ML, including the available learning algorithms. Moreover, we describe various ML types techniques.

ML is a science concerned with the study of algorithms that employ statistical methods to enhance the performance of computerised systems by leveraging past experience [68]. The use of ML techniques enables computerized systems to generate unique patterns and inferences to effectively execute the desired operations. Over the last few decades, ML techniques have enjoyed wide application to address a variety of classification and prediction issues, and have generated accurate outcomes in terms of performance [69], [70]. Based on the type of activity performed, ML approaches can be categorized into three, namely classification, regression and structural. First, classification approaches are divided into binary classification approaches and multiple classification approaches. Besides, regression or prediction approaches are characterized by numerical output nature which cannot be computed. However, the result of structured learning approach cannot be fixed based on length.

Based on the parameters under consideration, ML approaches can follow two categorizations including linear and non-linear approaches. A linear approach is a somewhat simple approach with a defined role, and forms the basis for non-linear approaches. One of the most popular non-linear ML approaches includes deep learning (DL) approach [24].

(i) Categories of Training Methodologies: To investigate the training process of machine learning algorithmic frameworks, three different categories of training methodologies can be employed, including unsupervised, supervised and reinforcement learning, each of which is described in the next part of this subsection.

Supervised Learning Technique: The design goal of the supervised learning (SL) techniques is to construct a numerical framework using a labelled training input data sample, and the corresponding output. Basically, a supervised learning algorithmic technique is fed with a given labelled input data, with the aim of inferring or predicting the unknown target function (quantity) that does the mapping of the labelled training input samples into corresponding output labels. Examples of the predicted function include regression and classification of the category in an already defined set of labels. The above capability can be realized through optimization of the NN parameters by supplying training data.

Unsupervised Learning Technique: The unsupervised learning (USL) technique is designed with the goal of constructing a numerical framework using the input training data samples without the corresponding output samples. USL differs from SL in that it has no target goal prediction, but the aim is to infer a NN model that could have generated the training samples. The requirement is to reveal the hidden pattern in the unlabelled input data. It emphasizes the use of unlabelled training data to generate information by way of clustering, through resemblance within the observation points. To throw more light, one can consider the clustering of ungrouped data samples and the creation of new samples through learning the accurate distribution of data. A generative model is an example in this category.

Reinforcement Learning Technique: Reinforcement learning (RL) is a ML technique that is modelled as a Markov decision process (MDP), with the design goal of supporting dynamic adjustment of the principal parameters to maximize reinforcement indicator (or signal). Principally, the RL technique represents a reward regulated conduct learnt by an RL agent using a trial-and-error mechanism, to perform actions and collect cumulative rewards, by interfacing with the environment [24], [70], [71].

To achieve the target goal, a reinforcement learning systems (RLS) employ a RL agent in an environment to perform an optimal action at a specific current state, based on the interaction between the agent's action and the state through the environment. Unlike traditional ML methods, RL has no instance of input data. The need to maximise the reinforcement indicator generated from the environment can produce a decent or bad evaluation result of the action, as opposed to informing the system to generate the right action.

The RL technique is assumed to be appropriate in circumstances where the input data is delayed. Moreover, RL is beneficial in that it can perform much as there may be lack of sample unseen training input and output data. But, it is unfavourable because it takes long to attain convergence [71]. Today, RL techniques has become an essential ML approach, which is widely employed in addressing network-oriented problems. One should observe that the techniques can only characterise the interplay procedures as opposed to availing another learning approach. Also, every learning algorithmic

TABLE 6. Comparison of the three training methodologies.

Training Methodology	Description	Advantages	Disadvantages
SL [73][74]	Represents the machine learning activity of predicting a target function based on an existing labeled training input data set commonly defined by human expert.	• Discovers concealed trends minus of the need to rely on labelled data • Does well in case of new data as opposed to the supervised approach	• Needs a data set which represents the system • The data is physically labelled by human experts, making it unsuitable for various real-world use cases
USL	Represents the machine learning activity of predicting a target function to describe a hidden structure in unlabelled data.	• Discovers concealed patterns without relying on labelled data • Performs better for unseen data compared with supervised approach	• It may not provide a useful insight into the hidden patterns and what actually they mean
RL[75]	Represents the continuous task of labelling and updating of real-time generated data to ensure the machine or deep learning structure can constantly adjust to changing inputs and outputs and again increase the delayed reward.	• Dynamical adaptation and gradually refinement • An agent interacts with an uncertain environment, in which the goal is to maximize the agent's reward. It can also be used for difficult problems that have no analytic formulation	• There is a trade-off between exploration and exploitation. In addition, we need to specify a reward function, parameterized policy, strategy and initial policy

model can be transformed into a RL, and is envisioned to be widely employed for traffic analysis and prediction.

To illustrate the use of RL in the maximization of the predicted cumulative reward, we can consider Q-learning. By performing Q-learning, one can maximize the Q value for the respective states. But, a major problem in the use of Q-learning involves the state dimension explosion. Precisely, the larger the state dimension, the more the computation required to be performed. In an attempt to address this problem, recent works have employed deep Q-learning by employing the NN to estimate the Q-function and generate the Q values from the state. Such RL techniques based value undertake action merely by using Q-values which are not essentially needed. The alternative is to perform straightaway policy learning which maps individual states into optimal actions. This technique termed policy-based RL learning, but the accompanying problem is the variance that enlarges extensively [76].

To deal with the problem of computational complexity and state explosion problem, actor-critic RL technique is employed. The actor-critic technique leverages a combination of NN that trains a policy (actor NN) and a second NN which evaluates the corresponding Q value (critic NN). Due to the generic nature, RL domain is studied in other different specialities that may include information theory, game theory, control theory, operations research, simulation-oriented optimization smarm intelligence, multiagent systems, statistics and hence genetic algorithms. The relationship between DL, ML and AI is as given in Fig. 3. Provided in Fig. 4 is a summary of the available DL techniques [24], [75], [77].

B. DEEP LEARNING

This subsection focuses on deep learning (DL) and the related algorithms. Moreover, we describe various DL techniques which are applicable to current and future SDN-enabled communications networks.

Deep learning is a subdivision of ML whose aim is to devise machines with the capability to interact with the environment, even when unexpected situations take place [78], [79]. Essentially, the DL approach can be used to perform prediction, classification and decision making using available data without any explicit programming.

DL techniques employ multi-layered neural networks composed of input, hidden and output layers for constructing interrelated neuron-driven nodes. They can be used to address diverse and difficult problems typically encountered in the ICT industry. Normally, contained in the nodes are activation functions. In terms of implementation, the information is input by use of the input layer. Subsequently, the hidden layer deals with pattern recognition activity through the use of activation function, upon which the decision outcome is forwarded to the output layer. Recall that every layer in the system takes in the output from the preceding layer as input, upon which the non-linear transformation is applied to generate important feature necessary to support the classification process.

Typical DL techniques include k-nearest neighbours classifier, regression, and Q-learning. Different from traditional ML tools which are heavily dependent on features that are defined by area experts, DL algorithms hierarchically mine knowledge from the available raw data using a multiplicity of

TABLE 7. Summary of the traditional ML algorithmic techniques.

Algorithm	Description
NC	This performs the computation of the centroid for every labelled class. Moreover, it computes the distance from the observation point to the centroid. Subsequently, it assigns the data points to a given class to the class having the shortest distance to the observations
NB	Represents a simple probabilistic classifier that relies on the implementation of Bayes' theorem. Moreover, it is used to during is a condition when the data dimensionality is high, given the assumption that the data features are independent of each other
DT	Represents a simple algorithm which implements a decision classifier using a tree-like technique, with corresponding leaf nodes to the class label, and the path between the tree roots and the leaf are connected using the classification rules
RF	Represents an extension of DT which groups few DTs and resolves the problem of overfitting by performing random selection of a subset of data features
SVM	Represents a binary classification and pattern recognition algorithm which performs the mapping of the data points in n-dimensional space and hence plotting the hyper plane which divides them into various clusters
MCSVM	Normally, SVM is employed as a sequence of binary problems to separate the data into more than two classes. But, because this requirement is computationally expensive, there are novel methodologies which have been devised to address this problem.
LapSVM	Represents an extension of SVM which harmonizes the SVM using Laplacian graph.
AdaBoost	A boosting approach which constructs more accurate algorithms by developing a hybrid classifier from the week classifiers.
G-AdaBoost	Executed based on three steps that include loss function optimization, predictions based on a weak learner, and loss function minimization using the hybrid model built from the weak learners.
M5Rules	Accessible from Weka software. M5Rules undertakes decisions for prediction problems by integrating decision trees with linear regression.
LR	Linear regression is an algorithm that is employed to predict and forecast purposes. It is used in an effort to fit a model to data points by using an independent variable.
PR	Shifts a linear regression model into a curve to better fit the observation points
K-means.	Different from the rest of the supervised methods, K-means clustering, refers to unsupervised machine learning algorithm which divides the data into k dissimilar clusters, where individual data points are allocated to a cluster that has the closest mean value.

nonlinear processing units, predict of perform actions based on the defined goal. Today, the most popular DL techniques include neural networks (NN). Clearly, however, only NNs having two or more layers are regarded as deep techniques or models. Others deep NNs architectures or structures exist and these include neural processes, deep Gaussian processes and random forest. Principally, as opposed to ML, DL technology is beneficial in that it ensures automatic features generation, by which handcrafted feature engineering can be circumvented. The relationship between DL, ML and AI is as given in Fig. 3.

Deep Learning Algorithms: Provided in the rest of this subsection is a description of the various categories of deep learning algorithmic techniques.

i) MLP: This represents a feedforward neural network (FNN) where the output of individual layers is fed forward to the successive layer. The multilayer perceptron (MLP) provides the default (vanilla) baseline of the FNN. In MLP, the output of each perceptron is forwarded directly to the subsequent layer's perceptron's, however without of any recursion and computation besides the activation function. Much as the structure of MLP is simple, it can distinguish data that are not linearly separate so long as the number of perceptrons, precisely the NN model size is large enough. The training approach of a MLP is called backpropagation. By using backpropagation approach, the MLP is trained using gradient decent optimization algorithmic techniques.

ii) RNN: Recurrent neural network, RNN represents a category of NN where the output of a layer encounters internal recursions. RNN represents a form of multi-level perceptron (MLP) which is made up a feedback loop at the hidden layers. Similar to the behaviour of humans, RNN performs a decision by taking into account the available information and the previous experience obtained through the inbuilt loops. They are designed to maintain the input given to the internal memory that it so contains. RNN operates

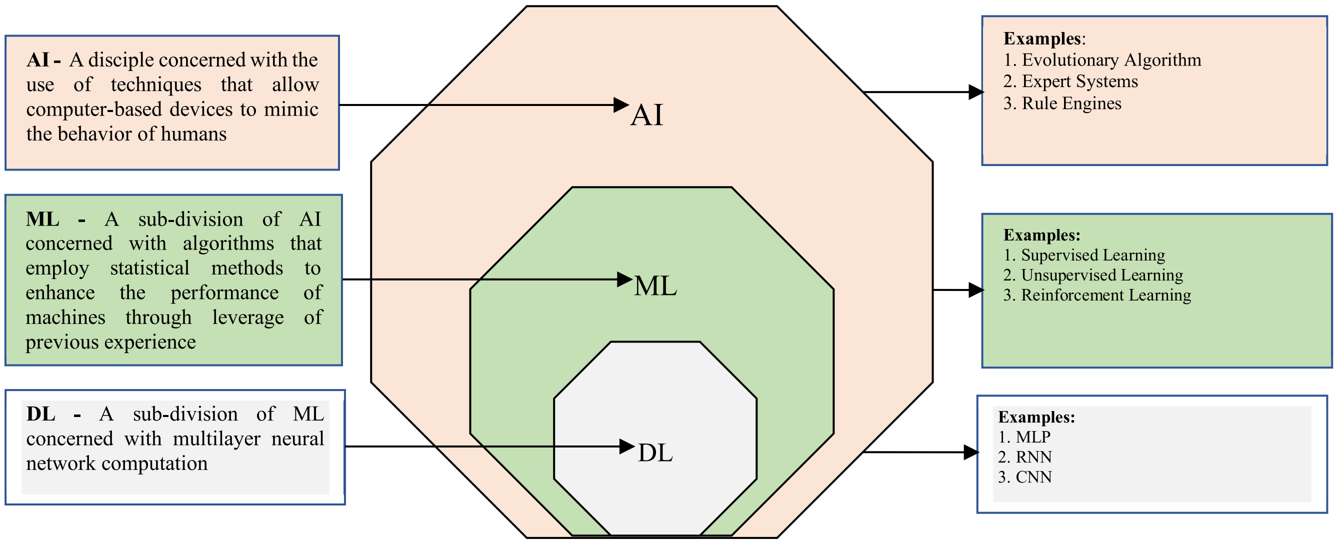

FIGURE 3. The relationship between AI, ML and DL.

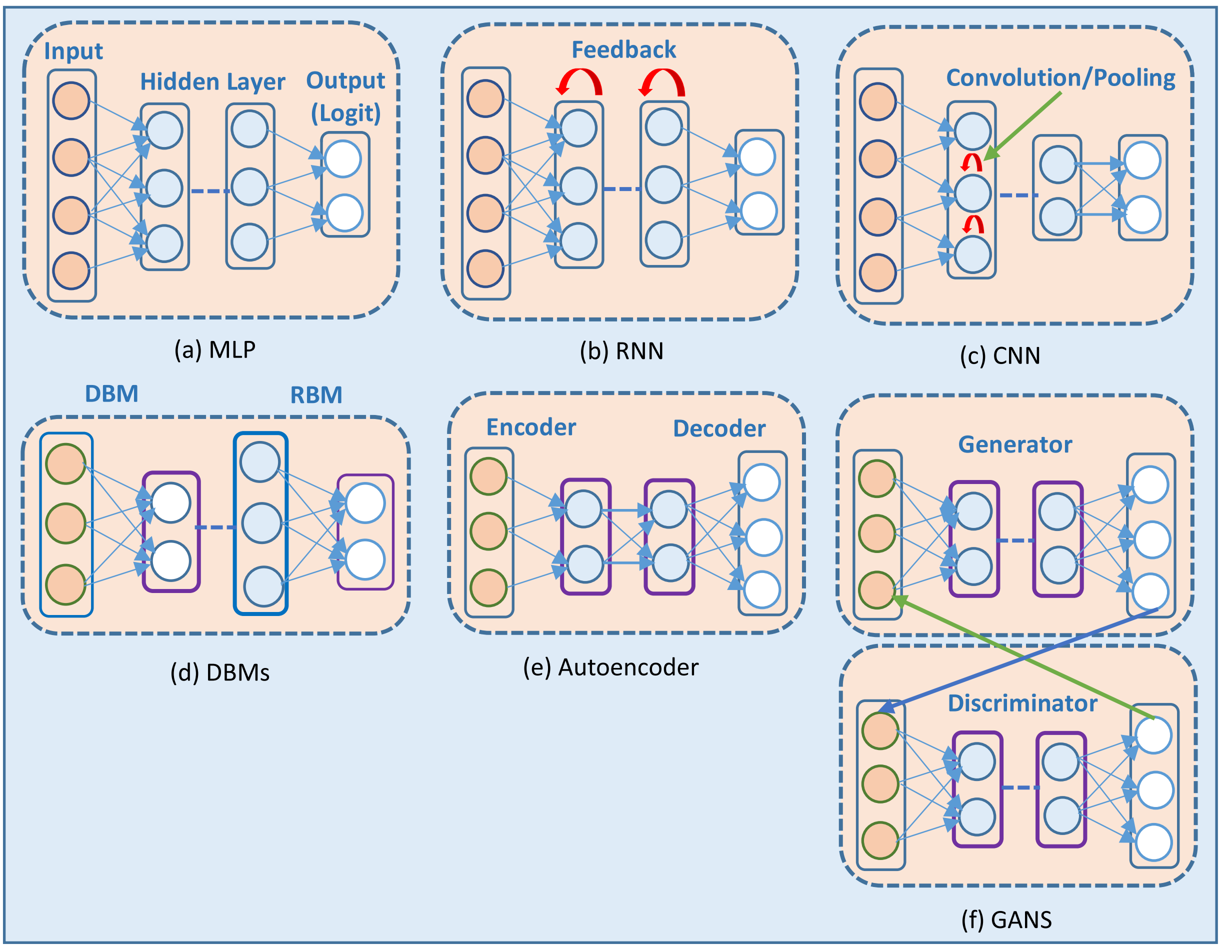

FIGURE 4. DL techniques.

by backpropagation of the computed errors by the layers to train and learn in a recurrent way. The training process of RNN requires the hidden layers to be sequentially stretch out. This requirement allows previous hidden layers to the feedback loop to be connected to the hidden layer subsequent to the loop. The connectivity construction supports a series of inputs, which is acceptable. Currently, varnishing gradient problem is a major challenge to vanilla RNNs. The vanishing gradient problem emanates due to inability of the iterative feedback loop to generated a feature containing long-term correlations. The solution requires the embrace of long short-term memory (LSTM) unit to replace the hidden layers in vanilla RNN [77]. By using the LSTM unit a memory cell is incorporated to store values for the current hidden layers in memory, which memory is under the control of various gates that ascertain the need to perform storage of forget. Similarly, gated recurrent unit (GRU), equipped with gates can be employed to perform the same operations [80].

iii) CNN: Convolution neural network, is a category of NN designed to resolve the problem associated with the generation of a large number of MPLs required to process a large number of image-based data samples. The motivation of CNN construction is based on the following three concepts: the convolutional layers, weight sharing layers and pooling layers. To address the problem, CNN incorporates two processing layers which are stuck between the hidden layers. First, the convolutional layer employs the convolutional operation to process the information input and perform feature extraction. This is done in addition to information compression. Second, the out of the preceding layer are pooled into one perceptron in the subsequent layer, by selecting the maximum value or using their average value [81]. Third, feature information so compressed is reverted to a convolutional MLP construction to generate the output, resultant forming connected layers. Precisely, whereas the convolutional and the weight sharing layers work as filters to extract local features in the data and hence reduce the parameter numbers, the pooling layers additionally minimize the feature dimension and maintain the variation of the data.

iv) Autoencoders: Autoencoders (AE) represents unsupervised learning techniques that handles the encoding of the data through dimensionality reduction. The purpose of AE is to train the network by rebuilding its input. As provided in the figure, the primary NN performs the learning of the representative input data features, called encoding. Next, the NN obtains the features in form of input to approximate the primary input as the ultimate output, called decoder. The emphasis of AE involves the learning of valuable input data features, intended for replication of the input. So, need to exactly reproduce the same output like the initial data can turn out to be extremely accurate to extract the hidden features. The variations of AE include stacked, convolutional, contractive, denoising and sparse.

v) DBN: Deep belief network, DBN is a category of neural network designed to address the infamous vanishing gradient problem experienced when training a deep NN [82]. Using DBN, the vanishing gradient problem is addressed by employing the divide-and-conquer technique. Initially, the network is partition into subnetworks called restricted Boltzmann machine (RBM), each of which is individually pre-trained. Subsequently, are RBNs are pooled and entirely fine-tuned. The outcome of this is a pool of pre-trained RBMs. every RBM is constructed of one hidden layer and one visible layer which take in input or generates outputs. The two layers are bidirectional connected. This marks the difference between RBN and FNN. Following pre-training process, the individual RBNs are strategically combined to connect each RBN's hidden layer to the following visible layer. This makes a DBN to be an FNN. Moreover, by extending a DBN, a CNN construction can be realized, mainly by partitioning individual hidden layers into several groups and employing a convolutional operation for each group.

vi) GAN: Generative adversarial network (GAN) represents a generative category of NN in USL charged with the role of generating first-hand data samples given by the predictable distribution of the input data samples [83]. The above is realized through training two NNs RNNs, precisely the generator and discriminator, like the perform a zero-sum game. On the one hand, the generator does the faking of data samples used to fool the discriminator.

On the other hand, the discriminator attempts to identify the faked samples. As the faking and discrimination games gets to equilibrium, precisely completion of the training process, the generator attains the capability to produce fake but genuine samples that cannot be distinguished from genuine samples.

As provided in the Table 8, the most commonly used DL algorithmic techniques are RNN, CNN, AE and DRL. Besides, DRL and RBN are algorithms constructed based on two techniques. Lastly, MLP and RBM represent algorithmic techniques which have not yet gained popularity in terms of use

TABLE 8. Categorization of deep learning techniques.

Categorization Criteria	DL Technique
Popular DL Techniques	• RNN • CNN • AE • DRL
Multifaceted DL Techniques	• DRL • GAN
Least Popular DL Techniques	• MLP • RBN

C. META-HEURISTIC ALGORITHMS

Currently, heuristic algorithms have dominated current network solving situations. Such algorithms are employed to address problem-specific issues. With the increasing complexity of modern network HA cannot suffice. To bridge the gap, the growing embrace of meta-heuristics provides a suitable alternative. Different from existing heuristic, meta-heuristic refers to general purpose approach, geared towards resolving a diversity of problems that cut across disciplines, that may include accounting and finance, through science and engineering to communication networks [84].

Recently, the application of meta-heuristics has increasingly gained popularity in solving complex optimization problem [85], such as those in modern large-sized dynamic networks. Basically, such approaches are focused on problem solving conditions that cannot be resolved using deterministic or exact technique, moreover within reasonable time scope. By background, meta-heuristic approaches are motivated by and are applicable in complex problem solving situations. Such situations may include optimization problems that include combinatorial and extremely non-linear and multi-modal scenarios [86].

Given that various meta-heuristic algorithms possess different capabilities, they provide different levels of benefit. So, the need to generate better benefits in terms of outcomes demand for the embrace of integrated strategies [85]. As mentioned in [84], such a strategy emphasizes a trade-off between exploration and exploitation. While exploitation involves the determination of the most likely high quality outcomes in the search space, exploration considers the need to perform a search in specific areas, based on past search outcomes. A major drawback of meta-heuristic approaches is the fact that it can barely suggest a good outcome and not the most optimal solution with certainty. Besides, such approaches rely on the definition of a large number of hyperparameters that need fine-tuning, to generate a good outcome [87]. The rest of this part is dedicated to some of the common meta-heuristic algorithms.

1) ANT COLONY OPTIMIZATION

Ant colony optimization, which is ACO for short refers to a meta-heuristic based swarm intelligence population-driven algorithmic technique used to address combinational optimization problem-solving situations [97]. The inspiration behind the ACO algorithm is by nature related to the foraging behavior of ants. Initially, the ants embark on a random exploration of the area that surrounds their resident nest. Then, they select specific path along which they deposit a chemical pheromones trace, to guidance the rest of the ants to food sources that previous ants discovered. Over a given time, duration, there occurs an increase in the concentration of the pheromones on the shortest food source path. The evaporation of pheromones is useful because it overcomes the concern of premature convergence [84].

2) EVOLUTIONARY ALGORITHMS

The Evolutionary Algorithm also referred to as Evolutionary Computation (EC) represents optimization algorithmic techniques inspired by Biological Science and more so advanced in the context of Darwinian theory of the capability of nature to select (adopt) and ensure survival of the fittest [84]. Precisely, the area of EA encompasses evolution approaches, evolution program design, genetic algorithms, and genetic program design.

3) GENETIC ALGORITHMS

Genetic Algorithm (GA) techniques represent one of the most renowned and dominantly applied population-driven meta-heuristic techniques in this category [89]. Basically, GA uses Biologically inspired genetic material called a chromosome to represent an optimization problem solution. When several chromosomes are grouped together, a population is generated. The application of GA is based on two important operations, which include crossover and mutation. First, the crossover operation integrates formerly selected characters through exchange of some of their parts. Besides, mutation considers the randomization of the search procedure to avoid the issue of local optima. Observe that to better execute a GA, it is imperative to consider two factors that include the selection approach and the kind of crossover and mutation mechanism [84].

4) PARTICLE SWARM OPTIMIZATION

The particle swarm optimization algorithm which is shortened as PSO, represents another meta-heuristic algorithm that is based on swarm intelligence and population-driven strategy [90]. Basically, the PSO algorithm that imitates birds' flocking behavior to devise solutions to optimization problems. The realization of PSO features a swarm which is composed of N particles, which are stochastically generated from within a given search space. In PSO, the respective particles are identified using a velocity, a location, with memory to store and recall the best positions or solutions. Much as PSO has exhibited success in the determination of optimal regions in the search space, the feature to enable convergence on optima is still lacking.

5) SIMULATED ANNEALING

Besides the above, simulated annealing (SA) represents a met-heuristic solution that presents a single solution. The motivation of the algorithm is based on the annealing strategy used to provide a suitably well-ordered solid state of least energy [91]. Moreover, to minimize the objective function of the target problem in SA, the temperature parameter T is introduced. This is a key parameter in the algorithm [84]. For each iteration, the SA algorithm randomly chooses a resolution at the neighborhood of the current solution. To determine the acceptance level of the new solution, the objective function value is used, and the T parameters value, which drops in the progression of the search process.

6) BEE COLONY OPTIMIZATION-BASED ALGORITHMS

These represent innovative swarm intelligence-driven meta-heuristic algorithmic techniques whose development is foundation on cooperative honey bees' behavior. The bee colony optimization algorithm is mainly inspiration by the collective behavior of honeybee colony [84]. A well-known and popularly used algorithm in this category is the artificial bee colony (ABC). ABC is a popular foraging-motivated optimization algorithm, which employs the decentralized foraging behavior of bees to perform optimization. Moreover, a more interesting consideration in this case is the requirement of honey bees to ensure a trade-off amidst the exploitation of already recognized food sources and the exploration of possibly improved food sources at the neighboring settings.

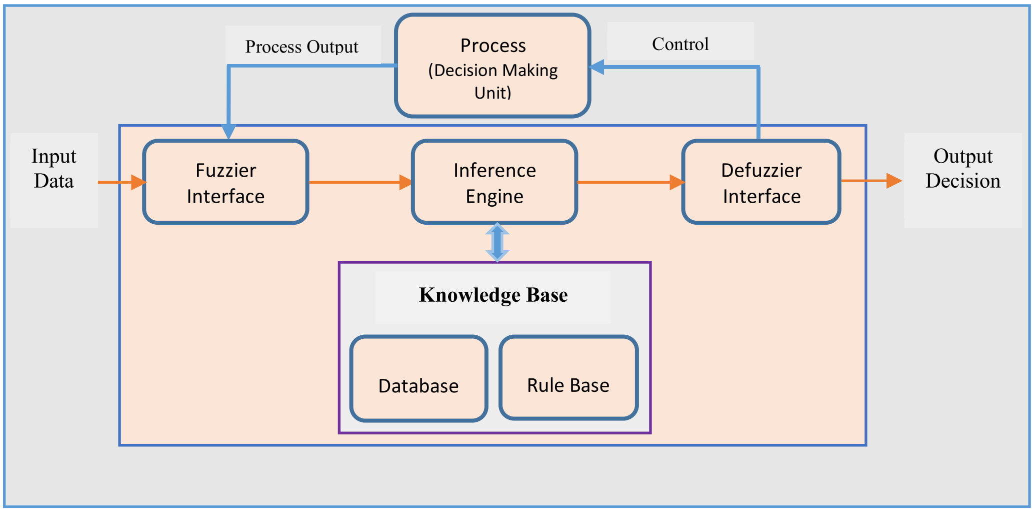

FIGURE 5. Structure of fuzzy inference system.

Generally, a beehive consists of bees which are grouped into three, including the employed, onlookers and scout bees. Moreover, the total number of employed bees is equal to the total number of food sources that are available. Assuming a particular source of food is drained, an unemployed bee becomes a scout bee, to randomly begin a search for new food sources. Additionally, the employed bees perform information exchange regarding food sources with a certain probability, using the waggle dance [84]. The ABC provides a global search capability which is realizable based on source production mechanism [92], [93]. Other meta-heuristic algorithms include Grey Wolf Optimization (GWO), Bat Algorithm (BA), Teaching Learning Based Optimization (TLBO), Firefly Optimization (FFO) and Whale Optimization Algorithm. For further reading, details of these meta-heuristic algorithms can be found in [94].

D. FUZZY INFERENCE SYSTEMS

This represents a system which relies on the application of the principle of fuzzy set theory to achieve the mapping of an input variable to the appropriate output. Different from classical binary logic where a given fact is true or false, fuzzy logic (FL) is a multi-valued logic which is concerned with the degree of truth or membership. To illustrate this, we can consider mapping of values in the range of 0 to 1 [95]. Moreover, we can consider Boolean logic as a unique example of FL. Basically, FS employs fuzzy rules to make use of fuzzy rules to perform the representation and mapping.

By composition, as illustrated in Fig. 5, the construction of fuzzy inference systems is based on four key components that include fuzzier, inference engine, fuzzy rules and defuzzier. Whereas the fuzzier accepts input variable, the defuzzier is concerned with the output of the desired value in the mapping. The use of fuzzy systems provides the main benefit of human-like manner of knowledge representation and the ability to explain. However, fuzzy systems lack the ability to adjust their behavior in-line with the changing environment. Moreover, the construction of these architectures calls for continuous tuning of fuzzy sets and fuzzy rules to match specific requirements. Today, there is an urge to embrace hybrid approaches, particularly neuro-fuzzy systems in combination with the learning power of NN, and the representation and explanatory capabilities of fuzzy systems to produce better outcomes.

Summary: The previous section has considered the basics of ML and DL techniques. We provide a description of the various ML types and common ML techniques that include the sub-division of DL, to give insight into these data-driven technologies.

V. EVALUATION OF SELECTED ML AND DL STUDIES IN SDN-ENABLED NETWORK

This section is dedicated to evaluation of carefully selected key SDN-enabled supervised ML and DL-based frameworks in the context of traffic prediction, flow routing and QoS-guaranteed with energy-efficiency.

Recently, traffic prediction, energy-efficient routing optimization and QoS provisioning have developed into essential areas of network traffic management and control, an aspect which has continued to register increasing levels of ML and DL application.

A. ML AND DL TECHNIQUES FOR TRAFFIC PREDICTION IN SDN

This subsection focuses on SDN-enabled network traffic flow prediction frameworks that employ ML and DL techniques. Recently, traffic prediction has developed into essential areas of network traffic management and control which has continued to register an increasing level of ML and DL application.

Given that SDN controller is limited to ensuring network intelligence through its programmability and global visibility feature, it can only allow the semi-automation of simple to fairly complex tasks. For network conditions that demand for complete automation of complex decisions, for instance in the case of large-sized dynamic networks, the management and control of such tasks can be delegated and handled through ML and DL schemes, since they are capable of performing the required analyses based the huge volumes of data in real-time, to perform better global routing decisions and achieve outcomes with higher levels of accuracy. Given next is a discussion of the most recent ML and DL algorithmic frameworks in such SDN-enabled networks:

Moreover, Oliveira *et al.* [96] investigated an algorithmic framework that employs ANNs to address the issue of traffic forecasting based in a general Internet scenario. Based on the work and by using general Internet traffic data, RNN revealed more superiority and suitability over stacked AE for performing time-series network traffic prediction. But, it was observed that to leverage the benefits of ML in the embrace of intelligent management of 5G network, there is need for a more complete study, using mobile traffic dataset is needed.

Zhao *et al.* [97], studied traffic matrix (TM) prediction in communication networks and suggested a DL framework which uses LSTM and RNNs to characterize the network spatial-temporal features. The authors proposed a new TM prediction framework which employs LSTM-RNN and linear regression method in a typically large-sized network scenario. The framework was trained and validated based on real-world dataset generated from Abilene network topology.

Azzouni and Pujolle [98] proposed NewTM, precisely a dynamic traffic matrix (TM) prediction framework that employs LSTM-RNNs technique to achieve future TM estimation, in large-sized networks. Basically, TM prediction targets the estimation of future network TM, using previous and current data traffic. This is largely employed in the scope of network planning, resource management and security provisioning. Accordingly, LSTM has become an appropriate and hence popular RNN design for data training and classification or prediction of time series with lags of unknown dimension. Precisely, LSTM have proved capable of modelling long-term dependencies, with much accuracy in comparison traditional RNNs. Unlike the previous work which wasbased on real-life data traces from Mininet simulator of GAENT network topology [98], this work employed data generated from GAENT backbone network traffic. In terms of performance, the framework was validated on real-time network data, and it exhibited fast convergence. But, it reveals high level of complexity.

Bayati *et al.* [99] proposed an algorithmic framework where traffic is modelled at various time-frames, while employing Gaussian process regression (GPR). The aim was to reveal different patterns at different timescales. Data that features both short-time scales and long-time scales was employed to generate the prediction outcome. Two different datasets were employed and evaluation outcome revealed low error propagation values compared to similar algorithms in LSTM and convolutional LSTM. Perhaps, to resolve the error propagation problem in the time-step-ahead prediction, this characteristic can be adapted in future research works.

Tang *et al.* [100], investigated channel assignment problem in Internet of Things (IoT) and proposed a novel SDN-based algorithmic framework that uses deep learning techniques on the historical data to perform prediction of future network traffic load of the switches and network congestion and thus allocate channels to each link in an intelligent way. Their objective was to provide a flexible channel assignment scheme to ensure improved transmission quality for IoT network system. Originally, the authors employed a simple deep belief network approach and deep convolutional neural network (CNN) during the data training phase. Subsequently, a DL-driven predictive channel allocation algorithm was integrated to ensure intelligent routing of traffic flows.

Alvizu *et al.* [101] proposed a ML-based algorithmic framework which combines RL and MILP (mixed integer linear programming) to optimise resource allocation in a dynamic manner, in mobile metro-core network orchestration system scenario. They focused on the objective to ensure offline traffic flow demand prediction in such mobile network operator. They proposed a framework to predict traffic flows by dynamically allocating network resources (slices) in advance. Here, dynamism means the resource allocation based on network state variability. Also, the TM variations are predicted and used to computes qualsi-optimal assignment of resources in a pro-active manner. The outcomes reveal that the solution can decrease the optimal gap for virtual wavelength path and wavelength path per-hour.

Alawe *et al.* [102] suggested a novel algorithmic framework which employs ML techniques to anticipate traffic load variability through prediction, to scale 5G core resources. A novel mechanism is proposed to scale network resources in the core domain of 5G networks. To forecast the network traffic load forecasting, the proposed solution employs real-life training dataset of traffic arrivals, in a typical mobile communication network scenario for training a neural network. The solution uses two techniques, namely LSTM-RNN and deep neural network (DNN). Moreover, the study considered latency in the scope of system response to network traffic variability and delay so as to make sure new network resources are readied to use by the VNF reflect the traffic increases.

Kaushik *et al.* [103] proposed a framework which employs DNN to evaluate and predict traffic activity in a telecom network scenario. The authors employed a ML algorithmic techniques that uses auto-regressive integrated moving average (ARIMA) in comparison with various non-deep learning algorithmic frameworks. During implementation, the neural network model was constructed and implemented using Tensorflow library to achieve the functionality and Adam was used to optimize the loss function. Then, training and testing was performed based on a publically available open source big dataset from Telecom Italia, training and testing was performed.

TABLE 9. Comparison of SDN-based supervised ml and dl traffic prediction approaches.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Oliveira et al. (2016) [96]	Application: Network Traffic Prediction Learning Approach: Supervised Learning ML Algorithmic Technique: RNN Dataset: Time Series Measurement of general Internet Traffic Traces Findings: MLP-BP beat other techniques. The convergence time of RNN was 66.87% faster, with an accuracy of 8.4% as opposed to the next best approach	• There is lack of adequate mobile traffic data to conduct a more complete study to leverage ML benefits in the intelligent management of the novel 5G cellular network
Zhao et al. (2018)[97]	Application: TM Prediction Learning Approach: Supervised Learning ML Algorithmic Technique: LSTM-RNN Dataset: Real-Time Data from Abilene Network Findings: Produced state-of-the-art performance with a minor prediction error, as compared to other approaches.	
Azzouni & Pujolle (2018)[98]	Application: Traffic Matric Prediction Learning Approach: Deep Learning ML Algorithmic Technique: LSTM-RNN Dataset: Real-Time Production Backbone Traffic Traces Findings: LSTM-RNN performs better than linear forecasting models such as HW, ARAR and ARMA. The same is true for feedforward neural network (FFNN).	• Feature extraction using time-series data to perform network traffic prediction and routing is a challenge • The method has high complexity which compromises accuracy • Unsuitable for large-sized network deployments with high computational complexity
Bayati et al. (2018)[99]	Application: Traffic Prediction Learning Approach: Deep Learning ML Algorithmic Technique: LSTM-RNN Dataset: Real-Life Production Backbone Traffic Traces Findings: Produced a lower prediction error and higher accuracy than ARIMA, FARIMA, LSTM and ConvLSTM.	• Error propagation in the predictive time-step is still a problem and this worsens the longer the time lag scaling
Tang et al. (2018)[100]	Application: Traffic Prediction Learning Approach: Deep Learning ML Algorithmic Technique: LSTM-RNN Dataset: Historical Data Findings: Achieves a prediction accuracy above 85% with 15 switches. However, the convergence time is higher.	
Alvizu et al. (2018)[101]	Application: Traffic Prediction Learning Approach: ML and Deep Learning ML Algorithmic Techniques: RL and MILP Dataset: Historical Data Network Type: Mobile Networks Findings: Decreased the optimization gap to less than 0.2% and 0.45%, for virtual wavelength path and wavelength path per-hour respectively	• The solution does not take into account route changes and link congestion
Alawe et al. (2018)[102]	Application: Mobile Traffic Load Forecasting Learning Approach: Supervised Learning ML Algorithmic techniques: MLP, LSTM Dataset: Real-Life 5G Mobile Cellular Data Type of Network: 5G Network Findings: Relies on traffic forecasting to increase network scalability in 5G	• Does not consider the need to train the RNN how to evaluate the number of user plane 5G core network functionalities, needed to support the traffic at the data layer in such a virtualized setting

TABLE 10. Continued from TABLE 9.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Kaushik et al. (2019)[103]	Application: Traffic prediction Learning Approach: Deep Learning ML Algorithmic Technique: DNN, ARIMA Dataset: Big Dataset from Telecom Italia Type of Network: 5G Network	
Lazarus et al. (2019)[104]	Application: Time-Series Traffic Prediction Learning Approach: Deep Learning ML Algorithmic Technique: LSTM-RNN Dataset: Real-Life Production Backbone Network Traffic Traces from CAIDA and B4 of Google Findings: LSTM is more accurate compared to other approaches in terms of link throughput. Besides, it exhibits a quick per-link training time of up to 30 seconds and a reduction of x2 in MAPE compared to ARIMA	
Le et al. (2019)[105]	Application: Traffic Prediction Learning Approach: Deep Learning ML Algorithmic Technique: ConvLSTM Dataset: Historical Dataset with Missing Data Findings: Capture traffic flow trends smother than other algorithms. Achieves the best case accuracy with ER and RMSE of 35.0% and 40.5% less than LSTM. Achieves, R2 score 26.7% compared to LSTM in the best case scenario	
Chen et al. (2019)[106]	Application: Traffic Prediction Learning Approach: Deep Learning ML Algorithmic Technique: LSTM, GA Dataset: Big Dataset Type of Network: Mobile Cellular Network Findings: LSTM outperforms other approaches, producing MSE of 0.042%	• Does not consider application-oriented user perception and the allocation of resources in cellular networks

Lazarus *et al.* [104] conducted a detailed investigation and proposed an SDN-based DL algorithmic framework that uses LSTMs to aggregate and predict network traffic at short time scales, for future short-term decision making in TE in production networks. The focus was to address the current issue of short-term scales prediction requirement, which is different from traditional TM prediction approaches which are basically on longer-term time scales and so are much easier to predict. The framework was evaluated based on dataset of real network traces, by comparing the different variants of LSTM, including traditional network traffic modelling frameworks. Different levels of traffic aggregation and time scales were used in the evaluation.

Le *et al.* [105] considered the problem of traffic prediction in the backbone networks, with missing historical data. They proposed a novel DL framework that employs ConvLSTM to predict traffic flows in the backbone network. Different from existing approaches which basically capture ground-truth input from time-series data, the proposed framework leverages ConvLSTM to treat the spatiotemporal features of the TMs in the backbone networks, then build an architecture that conjoins the forward and backward ConvLSTM networks. Besides, the framework is built with an added model to determine the flow to be selectively measured in the future time frame. The proposed solution can perform corrective action on the data input to enhance the accuracy of traffic prediction.

Lastly, Chen et al, [106] proposed a DL genetic algorithmic (GA) framework that uses LSTM techniques to address the issue of traffic prediction in dynamically time-varying networks. The proposed framework is two-fold: first to employ LSTM techniques to extract temporal data traffic features. Second, to employ GA to identify the appropriate hyper-parameters for the build LSTM network. Ultimately, the authors successfully modelled a GA-LSTM network design for the prediction of traffic. Using a big dataset, the GA-LSTMs framework was trained and network traffic predicted.

This previous subsection has focused on and compared the different SDN-based supervised ML and DL traffic prediction approaches in SDN, a summary of which is provided in Table 10.

B. ML AND DL TECHNIQUES FOR ROUTING OPTIMIZATION IN SDN

This subsection focuses on SDN-enabled network traffic routing frameworks that employ ML and DL techniques. Recently, traffic routing optimization has developed into essential areas of network traffic management and control which has continued to register an increasing level of ML and DL application.

In communication networks, routing objective represents the principle function undertaken to overcomes link overload hence transmission delays, a condition which can ultimately compromise network performance. Of late, many researches have been conducted to address traffic flow routing problem. Given the use of SDN, the global visibility and programmability characteristics can be leveraged to flexibly configure the network switches and ensure flow routing to reduce traffic congestion and balance the load. Currently, two popular routing algorithmic frameworks are available: first, there exist Shortest Path First (SFP) algorithm which is a best-effort algorithm, which forwards packet based on hop-count or delay criteria; second, is the Heuristic Algorithm (HA). Although best-effort SPF algorithmic solutions are employed, they are not suitable for optimal resource utilization. Besides, HAs are employed in existing SDN networks, but a major challenged that is owed to the use of these algorithm regard their computational complexity. This condition can potentially overstretch the SDN controller during the flow-by-flow routing policy computation.

The recent advances and application of ML and DL techniques in SDN provide a suitable solution. In terms of benefit, ML-based solutions can be trained realize near-optimal routing solutions in a short time. ML algorithmic solutions are also advantageous because they are based on data-free model-driven to provide routing optimization optimal decision-making activities. So, RL techniques can be effectively employed to optimize routing decision. Additionally, supervised learning are employed to achieve routing optimization decisions. Provided next is a summary of the most recent studies that are related to predictive network routing optimization.

Huang *et al.* [107] proposed a supervised multitask learning (MTL) architectural framework to perform mobile-based Internet traffic prediction. The focus was to investigation how effective that framework is in performing spatial and temporal feature extraction. In terms of design, the proposed MLT-based DL network structure include LSTM-RNN and 3D CNN. A supervised MLT-based traffic prediction was conducted and evaluated using the big dataset from Telecom Italia.

Also, Sendra *et al.* [108], proposed an intelligent SDN-enabled routing framework that leverages RL to enhance routing performance. Their work emphasized the use of unique feature of SDN and pattern generation power of AI to improve routing in such networks. The author leverage the RL process to compute and select the best routing data delivery path using the best criteria, while considering the status of the network. The framework was implemented using the Quagga suite.

Stampa *et al.* [109] studied a SDN-enabled deterministic policy gradient (DDPG) routing algorithmic framework that leverages DRL and network traffic prediction to perform dynamic generation of the most optimal path from the DRL agent. Then, future traffic demand is performed using the popularly used LSTM. This was motivated by the need to optimize routing through the knowledge plane intelligence provided by SDN, in combination with ML and DL. These advances have provided options to resolve network challenges such as QoS-aware routing optimization of performance, in typically large-sized dynamic networks. To determine the state of DRL, they use the TM. Besides, the action is performed by the tuple upon the weights of the links. Then, the reward computation is derived from the average delay of the network. All these were determined by DDPG. The proposed solution revealed very promising performance, by providing the benefits of global network visibility. But, the work was dedicated to the minimization of the mean latency of the network, disregarding the problem of QoS routing using various metrics such as latency and packet loss rate. Also, the solution is complex especially in the cased of large-sized networks.

Azzouni *et al.* [110], suggested NeuRoute, a dynamic SDN-enabled RL framework that employs supervised LSTM-RNN learning technique for traffic matrix prediction and routing. The motivation involves the recent growing popularity of RL techniques in addressing the prediction and dynamic control challenges in the absence of labelled data. They proposed a controller-agnostic routing framework capable of learning a given routing algorithmic scheme and thus imitate its results through the use of neural network in real-time. The solution can in real-time perform traffic matrix prediction and hence train the NN to learn the features of flows. Ultimately, it extracts the forwarding rules to optimize the throughput of the network. The approach is effective and performs better than efficient dynamic routing HA through computation of the near-optimal shortest path in a short time, given the available data. But, it requires adequate inferred data to train the NN.

Mestres *et al.* [111] investigated the use of neural network to accurately model delays as a function of input network traffic. Based on ML techniques, a configuration-based search model is employed to satisfy the target policy requirement. Different neural networks designs where trained based on various network scenarios that feature units like network topology, network size, traffic intensity, and routing. This consideration is vital to formulate instruction bout how these neural networks are trained.

Mao *et al.* [112] proposed a novel SDN-enabled non-supervised DRL framework that employs DBN. The framework employs CNN technique to compute the best path combinations and thus improve path control in SDWNs. The goal is to alleviate the explosive traffic growth rates typical of modern large-sized network. The SDN controller is charged with training the CNN algorithm to learn how to adapt to the changing traffic patterns, and hence route traffic flows based on previous experience. In essence, the controller monitors network performance, captures the network traffic traces after executing the DL-based routing strategy, to periodically retrain the CNN algorithm. The CNN-based solution serves two roles: performing intelligent routing and self-adaption to network state variability. The solution repeatedly labels data capture in real-time, which is then used to retrain the DL-CNN network architectures. This process allow adaptability to network variabilities. In terms of outcome, the proposed solution can control network traffic as opposed to traditional routing algorithms, leading to superior quality service delivery. The solution performs better compared to legacy OSPF.

Sun et al [113] proposed an intelligent network control architectural framework that employs DRL to dynamically optimize routing plans in an SDN-enabled network without the need for human involvement. The proposed framework in called TIDE. It was deployed and validated on a real-world network scenario. Much as many routing optimization approaches have been devised over the years, most of these are complex in terms of application and cannot achieve optimal performance.

Hossain and Wei [114] proposed an SDN-enabled QoS-aware intelligent and situation-driven routing framework that leverages RL technique to address situation-aware and intelligent network routing management. Precisely, the framework is based on two algorithmic modules. The continuous QoS monitoring (CQM) module and RL module. While the SDN-based CQM performs the monitoring of the state of the network based on QoS metric of the network (including packet loss and delay), the RL module performs intelligent routing optimization task. The solution can potentially ensure situation awareness, to overcome network challenges such as traffic congestion and resource overutilization.

Almasan *et al.* in [115] propose an a novel SDN-based OTN-driven ML and DL framework which combines the use of GNN and DRL to achieve routing optimization in communication networks. The objective was to optimize routing to ensure generalization in certainly not seen previously arbitrary network topologies. The model employs the GNN to represent or model the computerized network setting. The GNN was designed to extract useful information regarding the correlations between the network links and data traffic flow over the network topologies. Additionally, DRL is employed to construct an agent-based mechanism that is able to learn and generalize on how to optimize based on unseen network topology to achieve the desired goal optimization function.

Liu *et al.* [116] proposed an intelligent SDN-enabled routing framework based on DRL to address the issue of resource allocation and performance guarantees in traditional DCNs. The authors focussed on routing and traffic scheduling for the various traffic categories with different requirements in SDN-based DCNs. They constructed DRL-R solution based on deep Q-Network (DQN) and DDPG. Deployed at the controller, the DRL agent performs frequent interaction with the network to ensure adaptive and reasonable routing. The network state is employed to achieve optimal resource allocation to the incoming traffic. The evaluation results reveal the effectiveness of the DRL-R solution. Besides, the work leverages the global network view coupled with continuous learning to improve throughput by 40% over OSPF. While the flow completion time improved by up to 47%, load balancing reported an improvement of 8.8%. Overall, DDPG performed better than DQN.

Ali *et al.* [117] proposed a dynamic SDN-enabled DRL framework which employs deep double queue network (DDQN) algorithmic technique to achieve packet routing. The focus was to address the lack of scalability in the centralised path computation approaches and the lack of E2E performance awareness of the distributed approaches. They considered a hierarchical cluster-based dynamic per-flow path computation scheme by exploiting the DDQN algorithm, where E2E path computation is done at source nodes, with the help of cluster leader at the various hierarchical levels. The proposed solution can scale in large-sized networks and adjust to traffic demand variability, to efficiently employ network resources. Moreover, the solution is applicable to segment routing.

Sun *et al.* [118] proposed a SDN-enabled ML framework called SINET, that employs DRL to ensure scalability in the optimization of path routing. To achieve more robustness and scalability, the framework selects several key nodes, which are under the direct control of the DRL agent. Moreover, the agent performs dynamic generation of routing policies to optimization network performance. After training, the evaluation outcomes reveal that SINET solution can reduce the average completion flows by 32% in a network deployment of 82 nodes. It also exhibits robust performance against minimal time of network topology variability, when compared against similar DRL-based schemes.

Kumar *et al.* [119] proposed SDN-based ML algorithmic framework to ensure efficient routing of the required traffic flows. The proposed framework is composed of two subunits: first is the training unit which learns from the recently provisioned paths for a particular network state; second is the deployment unit, upon which the controller is enabled to perform queries at defined time intervals so as to select the finest path using the current network state, to provision new path with the help of the received information. Moreover, the ML unit performs adjustments to the network topology, to eventually make intelligent decision about traffic flow routing. Based on the account of network congestion and traffic pattern history, network traffic flow routing is done. Therefore, by using the proposed solution, a list of possible routes is constructed by the SDN controller through leverage of network traffic statistics.

Hu *et al.* [120] proposed an intelligent experiential SDN-enabled DL framework known as EARS to automate traffic routing. The focus was to maximise network utilization using throughput and delay metrics. The work considered various flow features to develop a DDPG-based automatic routing algorithm as DRL decision brain. The algorithm was used to determine the near-optimal paths that, respect to mice and elephant flows. The solution was evaluated in a real-life environment and the evaluation outcomes reveal a significant improvement in the network throughput, coupled with reductions in average packet delay, when compared against baseline schemes such as OSPF and ECMP.

Fu *et al.* [121] proposed a SDN-enabled ML algorithmic framework that employs deep Q-learning (DQL) to optimise routing path computation in DCNs. The focused on meeting the traffic demands of elephant flows and mice flows by considering throughput, latency and packet loss. To define the network state, they employed port rate and flow table utilization. To achieve the above requirement, Q-network was trained. The evaluation outcome reveals that the routing optimization solution can outperform ECMP routing and selective randomised load balancing (SRL) + FlowFit.

Zhang *et al.* [122] proposed a CFR-RL (Critical Flow Rerouting-Reinforcement Learning), a Reinforcement Learning based scheme that learns a policy to select critical flows for each given traffic matrix automatically. CFR-RL then reroutes these selected critical flows to balance link utilization of the network by formulating and solving a simple Linear Programming (LP) problem. Extensive evaluations show that CFR-RL achieves near-optimal performance by rerouting only 10%-21.3% of total traffic.

Provided in the previous subsection is a comparison of the different SDN-based supervised ML and DL routing optimization studies in SDN, a summary of which is provided in Table 11.

C. ML AND DL TECHNIQUES FOR QOS PREDICTION IN SDN

This subsection focuses on the related SDN-enabled QoS prediction frameworks that employ ML and DL techniques. The purpose is to give a summary of ML and DL QoS-guaranteed traffic prediction in the scope of SDN networks. Lately, QoS prediction has developed into essential areas of network traffic management and control, which has continued to register an increasing level of ML and DL application. QoS prediction is essential because it enables communications service providers such as operators and ISPs to estimate network performance to better deliver enhance QoT of services or applications, to ultimately improve customer satisfaction and overcome churn by customers. Some of the commonly used network-driven QoS metrics by communications service providers to measure network performance include throughput, delay, jitter and packet loss rate. Moreover, these metrics are related to network key performance indicator (KPIs) like queue length, packet size and the rate of transmission, among others. With the popularity of SDN paradigm, network operators can now leverage the centralized characteristic of SDN to capture traffic statics from the network switches in a fine-grained (port by port and flow by flow) manner. Based on the collected data statistics, ML algorithmic techniques can be employed to achieve QoS prediction.

Generally, by leveraging ML techniques to discern the quantitative correlations amidst KPIs and QoS metrics, network operators can be able to predict QoS parameters based on KPIs and enhance the management of QoS. One important observation is that, while QoS metrics are primarily continuous data, QoS prediction issue can be regression. Precisely, supervised ML has moved to the fore as a suitable technique for network QoS prediction. Provided next is a discussion of selected SDN-enabled ML and DL studies in the scope of QoS prediction:

Jain *et al.* [123] investigated the requirement to predict traffic congestion and suggested a multi-layer SDN-enabled QoS-aware routing (QAR) framework which employs M5Rules. The framework employs a combination of decision trees (DT) linear regressions to improve QoS management. The two-stage analytical framework features a multi-layer tiered SDN-based network application scenario. Moreover, the SDN control plane consist of a three levels of controller designed to reduce signaling-drive delays. The work considered efficiency, adaptability and packet forwarding application requirements. The proposed framework features a multi-dimensional analysis of key performance indicators (KPIs) from the networks and apply ML algorithmic schemes to automatically discover and extract new correlations, which are divided into estimated correlations, determined correlations and unpredicted correlations. Thereafter, root cause analysis of future network trends is performed to make traffic predictions. Basically, the approach is able: discover correlation data using big data analytics; make predictions; and support trend analysis. The proposed system is able to achieves better accuracy ration with minimal false alarms.

Lin *et al.* [124] proposed a multi-layer SDN-enabled DRL framework to ensure QoS-aware adaptive routing (QAR), in distributed hierarchical control plane architectural deployment. Different from the use of traditional Q-learning approach, the framework employed softmax action selection policy and state-action-reward (SARSA) algorithmic technique to ensure quality update. For every traffic flow, the centralized SDN controller performs update of the optimum routing policy by using the QoS needs and hence providing the forwarding table to every node along the forwarding path.

Yan *et al.* [125] proposed an SDN-enabled multi-layer on-demand network monitoring framework. The aim was to extend network analytics to the converged optical and packet network. In the design, big data analytical platform is employed to generate big data processing services. The framework also employs the network monitoring hub to capture and pool various monitoring information originating from the different layers for processing at the centralized server location. By using the on-demand network design, many network monitoring tools are provided in form of network services. Moreover, deployed at the SDN controller are the various applications that deal with the processing of the captured information, to enable multi-layer analysis by employing the SDN-enabled monitoring framework.

Carner *et al.* [126], proposed a ML framework that relies on traditional network model and NN model to estimate network traffic delay. To assess the performance, the researchers

TABLE 11. Comparison of SDN-based supervised ML and DL routing optimization studies.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Huang et al. (2017)[107]	Application: Network Forecasting and Routing Optimization Learning Approach: Supervised Learning ML Algorithmic Technique: LSTM-RNN and 3D CNN Dataset: Spatial-Temporal Big Dataset from Telecom Italia Network Type: Mobile Networks Finding: Mines geographical and temporal features from the data. Provides significantly high accuracy compared to traditional techniques such as ARIMA.	
Sendra et al. (2017)[108]	Application: Routing Optimization Learning Approach: Reinforcement Learning ML Algorithmic Technique: RNN, 3D CNN and CNN-RNN Dataset: Generated SDN-Driven IP Network Trace Driven Simulations	• The OSPF protocol convergence time rises due to the used implementation suit • The solution is tested in a virtual SDN network
Stampa et al (2017)[109]	Application: Routing Optimization Learning Approach: Deep Reinforcement Learning (Deep Q-Learning Using Actor-Critic Networks) ML Algorithmic Technique: LSTM-RNN, DDPG Dataset: General IP Network Trace Driven Simulations Type of Network: 5G Findings: Exhibited better performance than the initial benchmark	• The method has high complexity which compromises accuracy • Considers merely network delays, disregarding other important performance metrics like packet loss, throughput, energy-efficiency • Unsuitable for large-sized network deployments with high computational complexity
Azzouni et al. (2017)[110]	Application: Routing Optimization Learning Approach: Supervised Learning ML Algorithmic Technique: LSTM-RNN Dataset: Data Traces from Abilene Network Using Mininet Simulator Findings: Performs better than existing efficient dynamic routing HA when computing the near-optimal shortest path in a short time	• The method has high complexity which compromises accuracy • Effective but there is need for adequately explained or annotated data to train the NN • Considers merely network delays, disregarding other important performance metrics like packet loss, throughput, energy-efficiency
Mestres et al. (2018) [111]	Application: Software-defined Routing Optimization Learning Approach: Supervised Learning ML Algorithmic technique: RNN, Polynomial Regression Topology: One Directional Ring, Star & Scale-Free Network Dataset: Real-Life Production Backbone Traffic	• Lack of appropriate hyper-parameter tuning to accurately model average end-to-end communications network
Mao et al., (2018)[112]	Application: Network Traffic Routing Learning Approach: Imitation Learning ML Algorithmic Technique: DBN Dataset: Real-Life Network Data Traffic Network Type: Software Defined Wireless Network Findings: Performed better than OSPF, based on throughput and average hop-by-hop delay. Executes x100 faster when using GPU as opposed to CPU	
Sun et al. (2019)[113]	Application: Network Traffic Prediction and Flow Routing Learning Approach: Deep Learning ML Algorithmic Technique: DRL Dataset: Real-Life Network Data Traffic	• Does not take into consideration the mitigation of the impact of network related disturbances and service disruption due to flow rerouting
Hossain & Wei (2019) [114]	Application: Network Routing Optimization and Congestion Control Learning Approach: Supervised Learning and deep Learning ML Algorithmic technique: RL and CQM Dataset: Generated Real-Life Network Dataset Using Mininet Simulator	• Providing application-oriented QoS-guaranteed situation-aware network management and control mainly amidst cyber-attacks remains unresolved
Almasan et al. (2019)[115]	Application: Network Flow routing Optimization Learning Approach: Deep Learning ML Algorithmic technique: DRL, GNN Dataset: Rea-Life Topologies Data Traffic	

TABLE 12. Continued From TABLE 11.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Liu et al. (2019) [116]	Application: Network Flow routing Optimization Learning Approach: Deep Learning ML Algorithmic technique: DQL, DDPG Dataset: Rea-Life Topologies Data Traffic	
Ali et al. (2019) [117]	Application: Network Flow routing Optimization Learning Approach: Deep Learning ML Algorithmic technique: DRL Dataset: Rea-Life Topologies Data Traffic	• High complexity for large-sized network
Sun et al. (2019) [118]	Application: Network Flow routing Optimization Learning Approach: Deep Learning ML Algorithmic technique: DRL Dataset: Rea-Life Topologies Data Traffic	• Does not take into consideration the mitigation of the impact of network related disturbances and service disruption due to flow rerouting
Kumar et al. (2020)[119]	Application: Network Traffic Prediction and Routing Learning Approach: Supervised Learning ML Algorithmic technique: LSTM-RNN Dataset: Real-Life Production Backbone Traffic	
Hu et al. (2020) [120]	Application: Network Flow routing Optimization Learning Approach: Deep Learning ML Algorithmic technique: DDPG Dataset: Rea-Life Topologies Data Traffic	
Fu et al. (2020) [121]	Application: Network Flow routing Optimization Learning Approach: Deep Learning ML Algorithmic technique: DQL Dataset: Rea-Life Topologies Data Traffic	
Zhang et al. (2020) [122]	Application: Network Flow routing Optimization Learning Approach: Deep Learning ML Algorithmic technique: DRL (CFR-RL) Dataset: Rea-Life Topologies Data Traffic	• Does not support scaling concern in large-sized networks since it uses a LP model to generate rewards. The LP problem gets more complex with rising number of critical flows and increasing size of the network, hence slowing down policy training for larger-sized networks, since the required time for individual iterations can increase

employ the traffic load and the overlay routing policy to automate model training, to ultimately achieve network delay estimation. The evaluation outcome reveals that the NN-based estimation techniques outperform the traditional counterparts, when accuracy of delay is taken into consideration. Unlike the traditional regressor-based estimator, the human user can barely interpret the trained generic adaptive NN-based estimation solution.

Pasquini & Stadler [127] investigated and proposed an SDN-enabled ML framework that employs RG and RT to ensure application-aware QoS estimation. The two techniques were employed to estimate frame rate and response time parameters in video on demand (VoD) application. To perform the estimation effort, the authors relied on the generated device statistics, that precisely feature the operating system (OS), port and flow granularity.

Pasca *et al.* [128], considered the use of ML technique with the objective of achieving application identification. They focused on the classification of traffic flows by application-aware multipath routing approach for SDN-enabled networks. Moreover, the work featured controlled network resources such as bandwidth and low latency paths based on their specific priorities. An AMPS framework was proposed to automatically classify inbound traffic flows and employ QoS-based policy per flow, on the basis of its needs. The proposed solution consists of a Machine Learning Trainer (MLT) and Machine Learning Classifier (MLC), which are integrated into the SDN controller. The outcome reported an accuracy rating of 98% compared to other approaches, such as SVM, Bayesian Network, Naïve Bayes Kernel Estimation and Naïve Bayes. But, there was no report on the degree of precision, recall, and f-measure.

Pham *et al.* [129] proposed an SDN-enabled QoS-aware routing framework that employs DRL with CNN. This study was undertaken in the scope of knowledge defines networking (KDN). Moreover, the research effort was motivated by the highly complex requirement to support the much desired QoS-aware routing optimization, in the context of modern networks that feature many traffic flows which are coexistent in the same network. To address the issue, ML-based CNN technique was employed to capture the relationship between the network traffic flows and hence provide improved routing configurations.

Yao *et al.* [130] proposed an SDN-enabled network monitoring framework, that employs RL techniques to exert network control in an intelligent manner. Generally, the approach relies on big data analytical platform to support big data processing services. The drive was to resolve the issue of manual operational processes that characterize the configuration of forwarding approaches in SDN. The proposed solution leverages the SDN and network monitoring tools to build a fully centralized network view and exert management and control of physically separated network. Then a centralized intelligent-based agent is constructed to a provide network control policy through DRL. Precisely, the centralized intelligent agent is constructed to ensure policy learning through network-driven interaction. This requirement is vital to meet the much desired needs of modern large scale dynamic networks. The solution can provide self-learning control in SDN through the use of RL and network monitoring tools to generate dynamically network control policies. The concept of centralization enables improved application of ML in the network to resolve the network issues.

Al-Jawad *et al.* [131] suggested an SDN-enabled RL algorithmic framework called LearnQoS, which employs Q-learning for policy-driven network management. The focus is to ensure specific QoS optimization requirement for multimedia service provisioning. Three elements where considered to model the proposed RL framework, namely state, action and reward. The state is represented by the generated TM. Besides, to represent the agent, four various actions were considered: do nothing; upscale the data transmission rate; downscale the data transmission rate and perform a reroute. Moreover, the rewards were considered based on SLA constraints. Although the solution has network overheads, there was a major improvement in QoS performance, when compared against existing multimedia-enabled System.

The previous subsection has compared the different SDN-based supervised ML and DL QoS-based routing studies in SDN, all of which are summarized in Table 13.

D. ML AND DL TECHNIQUES FOR ENERGY-EFFICIENT ROUTING IN SDN

This subsection gives a discussion of some selected SDN-enable energy-efficient routing algorithmic framework using ML and DL. Featured in the works discussed are important system parameters such as QoS optimization, congestion control, delay and reliability. Recently, various researchers conducted a number of studies aimed at combining machine learning with SDN, details of which can be found in [132]. Following is a discussion of the recently selected SDN-enabled energy-efficient ML and DL studies:

Lin *et al.* [124] proposed a data center server-driven power utilization technique that leverages ANN. The study was motivated by the reactive nature of existing cloud-based server-oriented energy-aware scheduling approaches, a condition which leads to the lack of capacity to dynamically adjust to different workload variability. To address this, the authors conducted fine-grained and in-depth performance analysis that features power utilization attributes of the CPU, memory and server disk. In the analysis the considered the execution of various kinds of task loads. Different power utilization approaches were established based on BP, Elman and LSTM-ANN, respectively. To evaluate the performance, data from various kinds of task load were capture and used to train, validate and test the three power models.

Bayati *et al.* [133] proposed an improved multi-step-ahead energy-efficient framework to ensure predictive traffic demands forecasting. The proposed framework is called predictive adaptive link rate (PALR). The study was motivated by the undesirable reactive nature of current model-based energy-efficient routing frameworks, where the link speed is only adjusted on receiving a fresh traffic demand. Also, current energy-saving approaches put emphasis on energy utilization, disregarding the cost of network changes such as traffic routes and link rates during an entire session. Such a condition can lead to sub-optimal performance, especially in the future dynamic and large sized networks. With this condition, the requiring to ensure re-optimization during a session cannot be overemphasized, to improve the overall performance rating. To address the problem, the authors formulated an ILP approach and devised a simulated annealing scheme to compute its solution.

Bayati *et al.* [134] proposed a novel multi-step futuristic framework to predictively optimize link rates through traffic demand forecast. They formulated a multi-objective integer programming (MIP) mathematical model for energy-efficient link adaptation problem and proposed a heuristic simulated annealing algorithm to resolve it. The obtained result reveal that improved energy-savings with a significant reduction in re-optimization rounds in the energy-efficient routing. This work represents an improvement in previous link rate adaptive, emphasizing the effectiveness of link rate adaptation in network energy-savings though re-optimization of the traffic flow assignment process.

Covered in the previous subsection is a comparison of the different SDN-based supervised ML and DL energy-efficient routing studies in SDN, a summarized in Table 14.

E. HYBRID ML AND DL TECHNIQUES FOR IN SDN-ENABLED NETWORKS

This subsection gives a discussion of some selected hybrid or multifaceted SDN-enabled ML and DL algorithmic techniques. Various researchers have proposed many hybrid ML and DL architectural frameworks that employ at least two intelligent techniques to improve the overall performance of such algorithms.

TABLE 13. Comparison of SDN-based supervised ML and DL QoS-based routing studies.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Jain et al. (2016) [123]	Application: Routing Optimization with Prediction of QoS-driven Violations Learning Approach: Deep Learning ML Algorithmic Technique: Spearman's Algorithm, M5Rules and Linear Regression Topology: Hierarchical Core Network Model Dataset: SDN Dataset using Mininet Simulator Findings: Identifies various types of corrections.	• Not evaluated against other ML algorithmic counterparts
Lin et al. (2016) [124]	Application: Routing Optimization with QoS Prediction Learning Approach: Deep Learning ML Algorithmic Technique: DRL, NN Dataset: Generated an SDN Dataset Using Mininet Simulator	• Does not take into consideration the mitigation of the impact of network related disturbances and service disruption due to flow rerouting • Not evaluated against other ML algorithmic counterparts
Yan et al. (2017) [125]	Application: Network Traffic Monitoring and Control Approach: Deep Learning ML Algorithmic technique: DRL Dataset: Generated Real-Time Big Data	
Carner et al. (2017) [126]	Application: Routing Optimization with QoS Guarantees Learning Approach: Supervised Learning ML Algorithmic Technique: NN Dataset: Generated an SDN Dataset Using Mininet Simulator	• Generic Adaptive NN estimator is hard for human beings to interpret • Only considers delay, disregarding other metrics
Pasquini & Stadler (2017) [127]	Application: Routing Optimization with QoS Prediction Learning Approach: Supervised Learning ML Algorithmic Technique: RF, RT Dataset: Generated an SDN Dataset Using Mininet Simulator	• RF exhibits high computational complexity of overheads • Does not analyse others services such as real-time applications and video conferencing
Pasca et al. (2017)[128]	Application: Routing Optimization with QoS guarantees Learning Approach: Supervised Learning ML Algorithmic Technique: C4.5 DT Dataset: SDN Dataset from Experimental Simulator Network Type: SDN Network Findings: Realised an accuracy rate of 98% compared to other approaches.	• The work does not report on the degree of precision, recall, and f-measure
Pham et al. (2018) [129]	Application: Routing Optimization with QoS Prediction Learning Approach: Deep Learning ML Algorithmic technique: CNN, DDPG Dataset: Generated an SDN Dataset Using Mininet Simulator Network Type: Knowledge Defined Networks (KDNs) Findings: Effective in learning the correlations amidst traffic flows, hence improved routing patterns or configurations	
Yao et al. [130]	Application: Traffic Prediction and QoS-Based Network Monitoring Learning Approach: Deep Learning ML Algorithmic technique: RL	
Al-Jawad et al. (2018) [131]	Application: Traffic Prediction and QoS-Based Network Monitoring Learning Approach: Deep Learning ML Algorithmic technique: Deep Q-Learning	The solution has network overheads

TABLE 14. Comparison of SDN-based supervised ML and DL energy-efficient routing studies.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Lin et al. (2019)[125]	Application: Energy-Efficient Server Utilization Learning Approach: Supervised Learning ML Algorithmic Technique: BP, Elman and LSTM-ANN Dataset: Task-Based Dataset for Server Target Network: Cloud-Based Data Centre Network	• It is not trivial to optimise or tune hyper-parameters to accurately model average end-to-end communications network
Bayati et al. (2019) [133]	Application: Energy-Efficient Routing Learning Approach: Supervised Learning ML Algorithmic Technique: PALR Dataset: Historical Time-Series Dataset	• Faces time mode memory limitation, thus hard to train based on traffic flow time-series with an extended time lag train on traffic flow, which can compromise performance. With time mode memory limitation, the approach cannot support training and prediction of time-series with lags of unknown dimension (dynamic multi-step ahead time scaling)
Bayati et al. (2019)[134]	Application: Energy-Efficient Routing Learning Approach: Supervised Learning ML Algorithmic Technique: MOILP, SA Dataset: Historical Tine-Series Dataset	• Faces time mode memory limitation, thus hard to train based on traffic flow time-series with an extended time lag train on traffic flow, which can compromise performance. With time mode memory limitation, the approach cannot support training and prediction of time-series with lags of unknown dimension (dynamic multi-step ahead time scaling)

Sabih *et al.* [135] proposed an innovative hybrid SDN-enabled framework that employs intelligent-based techniques and ANN network architecture to investigate performance optimization requirement in such networks. The objective function was on maximal optimization of network performance and computational time. To select the best input set of network configuration for network efficiency optimization, the ANN architecture was trained using unseen data, taking into account the computational efficiency and performance index metrics in SDN-enabled network scenario. Then, the trained model was applied to study the behavior of the SDN network. Moreover, the two HA algorithms were applied independently: GA and Particle Swam Optimization (PSO). The outcome reveals that PSO exhibits better performance with a faster convergence time compared to GA.

Huang *et al.* [136] proposed an SDN-enabled framework which employs DNS response exploration and ML to achieve QoS-guaranteed application identification. They considered the application of a classification system which applies a polling strategy based on the use of RF, rotation forest, random committee with random tree. Their work was motivated by the increasing demand for application-driven management of QoS. Moreover, using the generated data of traffic flows, the system was evaluated and the outcomes shows that combined hybrid solution can achieve higher accuracy when compared against independent ML approaches. The proposed solution performs performed highly in terms of application identification accuracy. The average F-measure of 93.48% was reported.

Assefa and Ozkasap [137] proposed a hybrid SDN-enabled energy-efficient routing framework that employs ML and RL technique to improve link performance. The researchers considered a strategy where network traffic is represented as features, upon which feature size reduction can be performed using numerically proven algorithmic techniques, to provide heuristics that can potentially improve the accuracy assessment to 100%. The work modelled a dynamic SDN-enabled energy-efficient routing algorithm that use RL technique.

Yao *et al.* [138] proposed a hybrid SDN-enabled ML algorithmic framework that integrates a distributed intelligence control with a centralized intelligence control to provide various network services. The distributed intelligence is called AI routers, while the centralized intelligence is called network. Moreover, the framework deploys a centralized AI control to support connection-oriented tunneling-enabled routing protocol, like multiprotocol label switching and segment routing to provide high QoS. Besides, for the hop-to-hop IP routing, the intelligence control role is moved to the AI router, to minimize the control overhead exerted by the centralized control, and employ the network mind to improve the global convergence. The solution was evaluated by considering throughput, packet loss and link utilization. The results reveal

TABLE 15. A summary of hybrid supervised ML and DL studies in SDN-enabled networks.

Author	Objective, Mechanism, Metric, Emulation or Simulation Tool and Target Environment	Issues and Challenges
Sabih et al. (2017)[135]	Application: Network Optimization with QoS-Guarantees Learning Approach: Machine Learning ML Algorithmic Technique: ANN, GA & PSO Dataset: Unseen Data from Mininet Simulator Findings: PSO outperforms GA	
Huang et al. (2017)[136]	Application: Network Traffic Classification with QoS Guarantees Learning Approach: Machine Learning ML Algorithmic Technique: Weka Algorithm, RF, Rotation Forest, Random Committee with Random Tree (RT) Dataset: Network Dataset Network: Cloud-based CDNs Findings: The hybrid combination performs better compared to the stand-alone application	• RF reveals high computational complexity of overheads
Assefa & Ozkasap [137]	Application: Energy-Efficient Routing Learning Approach: Deep Learning ML Algorithmic technique: RL, HA Dataset: Historical Time-Series Dataset Findings: The hybrid combination performs better compared to the stand-alone application	• Complexity with regard to hyper-parameter definition • Approach is on traditional table-based agents which cannot support the need for efficient solutions in the condition of unseen network topology state, because the agent is unable to generalize and perform over unseen network states in unfamiliar network topologies
Yao et al. (2019) [138]	Application: Network Traffic Routing Learning Approach: Deep Learning ML Algorithmic technique: DRL	• Complexity in hyper-parameters definition is a major challenge.

that the hybrid solution can outperform baseline routing protocols like OSPF and ECMP.

VI. CHALLENGES AND FUTURE DIRECTION

The previous section covered the use of ML in SDN-enabled communication networks, including ML types, common ML and DL techniques and a discussion of selected supervised ML and DL-based studies, while featuring traffic prediction, QoS-guaranteed routing optimization and energy-efficient routing. This section is dedicated to a comparison of the most recent studies, identification of the relevant research challenges and a description of future research in transitional hybrid SDN/OSPF networks. The section is sequentially structured into research analysis and identification of current research challenges, followed by a description of future research direction.

A. GAP ANALYSIS AND EMERGING RESEARCH CHALLENGES

This subsection gives a summary of the research gaps identified and the emerging research challenges. First, the work identifies and summarizes the gaps and challenges of load balancing and energy-efficient routing studies conducted for hybrid SDN/OSPF networks, as given in Section III. Second, we identify and provide a summary of studies in the field of ML and DL in SDN-enabled networks, as detailed in Section . Based on this summary, we point out emerging research challenges.

1) ANALYSIS OF SELECTED LOAD BALANCING AND ENERGY-EFFICIENT ROUTING STUDIES IN HYBRID SDN/OSPF NETWORKS

The realization of fine-grained traffic prediction is an important requirement in the management and control of a wide range of TE functions [104]. Some of the important TE tasks that demand for enhancement in terms of network control and operations management include traffic flow routing, load balancing, energy-efficiency and QoS-aware service provisioning. The emergence of SDN architecture provides a suitable solution, however, complete deployment of SDN is currently unachievable. A preferred solution is hybrid SDN/OSPF networks, but it faces many challenges. Section III of this article has reviewed the most recent studies of load balancing and energy-efficient routing techniques for hybrid SDN/OSPF networks.

Provided in this part are the observations made given the analysis conducted to define future research directions. Based on the analysis conducted, an important observation made is that the majority of these studies have mainly featured model-based algorithmic solutions that employ generic QoS provisioning strategies. Such model-based generic solutions are constrained to the use of single QoS metric. Moreover, the model-based solutions employed are based on the use of traditionally configured network control plane mechanisms for traffic forwarding which can degrade network performance.

One of the key challenges faced in the optimization of energy-efficient routing while ensuring QoS guarantees is the slow network convergence and slow response to network variability in such hybrid SDN/OSPF networks. Today, the increasingly fine-grained network control requirement rapidly scales the network, and this is coupled with the exponential traffic growth. This makes traditional routing algorithms such as OSPF unsuitable for SDN, due to its slow convergence and slow response to network dynamicity.

Another challenge concernsthe development of model-based algorithmic approaches that support network traffic prediction and energy-efficient routing of a wide range of network traffic types, mainly due to the diversity of emerging multimedia services or applications. To provide support to the growing diversity of next generation user traffic and multimedia application delivery with strict QoS requirements, it is essential to combine all the important performance metrics, a condition which demands for the development of an integrated routing solution which considers all the key QoS metrics.

Additionally, selected energy-efficient routing solutions were reviewed and it was observed that the majority of these solutions have not considered the TE objective of load balancing. Also, many of these studies disregard the important requirement to collectively consider multiple important QoS metrics [67], [68]. However, owing to the need to distribute a growing range of next generation user specific services or application classes with strict QoS guarantees, more research should be conducted to develop innovative dynamic solutions. These solutions are essential in the quest for accurate operation of such hybrid networks, in order to achieve the desired network performance, mainly in terms of enhanced bandwidth utilization, improved energy-savings, throughput, minimal packet loss, improved throughput, low latency and jitter [53].

The increasingly fine-grained network control requirement can rapidly scale the network, moreover coupled with exponential traffic growth, a condition which makes traditional routing algorithms such as OSPF unsuitable for SDN, due to the slow convergence and slow response to network variability. The above condition challenges the optimization of routing while ensuring QoS guarantees.

2) ANALYSIS OF SELECTED ML AND DL STUDIES FEATURING TRAFFIC PREDICTION, ROUTING OPTIMIZATION, ENERGY-EFFICIENCY AND QOS PROVISIONING IN SDN-BASED NETWORKS

a: OVERALL ANALYSIS OF ML AND DL STUDIES

The current networking trends reveals that ML and DL techniques are gaining popularity in the management and control of communication networks, owing to current advances in two key innovative technologies, namely SDN [19], [20] and NA [25]. With the growing interest in the use of ML and DL techniques, a wide-range of network-based applications can now be supported. Such applications include traffic prediction, routing optimization, energy-efficiency and QoS-guaranteed service delivery.

As a recap, recent advances in ML have led to growing popularity in the use of supervised ML techniques in computer networking [24]. Although the effective use of ML techniques such as LSTM-RNN for traffic prediction can facilitate intelligent network management and control, parameter setting due to randomly changing nature of network traffic is a challenge, owing to the use of local optimization mechanisms [132]. This condition demands for a strong requirement to carefully set network parameters to ensure improved performance, based on high prediction accuracy in a typical dynamic large-sized network scenario. As an extension, the above condition requires balancing the trade-off between model training time and learning accuracy, to extract the finest design for the problem use case. The important parameters commonly considered include the number of hidden layers and the number of neurons for each hidden layer. As a possible solution, the recent integration of HA such as GA and DL has attracted considerable research interest because it enables more efficient selection of the hyper-parameters. However, many researchers are concerned about the inability of DL techniques to address the challenge of network variability. Perhaps, the use of RL can deliver a suitable solution, to improve network management and control.

In recent years, the literature has reported an increasing interest in the use of RL to improve network control and management [71], [72]. Principally, the underlying objective of the design of RL concerns the need to address issue of network variability and changes in the network state. Lately, some proposed RL-based routing solutions have reportedly outperformed other ML techniques such as DNN [139]. This comes as a major motivation to the embrace and advancement of RL for efficient network control and management.

As discussed in Section V, RL techniques have recently been leveraged to resolve the issue of traffic routing optimization in SDN-enabled networks [127]. Also, the use of RL has been reported in application areas such as energy-efficient routing in SDN-enabled networks. Other studies have considered the use of RL in addressing routing with QoS-guarantees [121], [130]. However, such studies are based on traditional table-based agents which cannot support the need for efficient solutions in the condition of unseen network topology state [108]. Traditional table-based agents normally perform based on a specific network topology observed in the course of model training. So, the agent is unable to generalize and perform over unseen network states in unfamiliar network topologies [138]. This observation is backed up by the reason that computer-based networks are primarily represented as graphs. Clearly, the complexity in hyperparameters definition remains a major challenge to the use of RL-based techniques, calling for practical solutions to be devised.

To address the aforementioned challenges, DRL algorithmic approaches have recently been investigated. In particular, DRL approaches such as Q-learning are increasingly gaining the attention of researchers as a probable solution to the existing challenges [109], [115]. Principally, Q-learning undertakes an action with the highest reward [139]–[141] and this has made many researchers to believe that a probable solution to the challenge of unseen network state is DRL [113].

Additionally, the iterative enhancement optimization process and heuristic through the use of DRL-agents is capable of providing near-optimal solutions in one step. With the recent progress in DNN [24], [114], [129], there has been considerable progress in the performance of DRL, in the scope of network control and management. This comes as a major motivation to embrace of DRL.

b: OBSERVATION AND LESSONS LEARNT

The aforementioned section has evaluated related works that employ various ML and DL techniques in SDN-enabled networks. Generally, it should be observed that current research on the application of ML and DL in SDN is a wide domain currently faced with several challenges. As previously stated, modern networks are characterized by intense uncertainties and dynamicity in traffic flow trends, and the operating circumstances of networking devices such as routers, network topology and the condition of wireless network channels. These different characteristics complicate the use of traditional ML techniques in modern network management and control.

Lately, the use of ML and DL technologies has become a reality in existing networks, but this development is still at its infancy. Due to this condition, the pressing need to devote additional research efforts toward the advancement of such technologies, in the modern networks cannot be overemphasised. The observation made is that, owing to the limitations of traditional ML and RL techniques, DRL provides a suitable option to deliver optimal performance in the context of modern large-sized communication networks. Unlike SL which emphasizes on traffic classification and regression activities, DRL is concerned about the target algorithmic models which can be trained and learned to determine the finest sequence of actions, for maximizing the objective function (target reward). As previously stated, a major motivation for the use of DRL technique is its suitability in resolving complex problems in modern dynamic and complex networking environments [139].

DRL offers a flexible means to support rich and wide-ranging diversity of applications which are traditionally based on dynamic system modelling and the interaction of multiple agents. Based on the observation made, we provide a vision towards the development and embrace of ML and DRL frameworks for the optimization of network performance. The above configuration leads to enormous space transitions and actions space in modern dynamic and complex networks. As a recap, the relevant approaches reviewed are summarized in Table 9-15.

Moreover, based on the above analysis, we observe that the problem of NUM in various network scenarios for TE and resource allocation are limited by different control variables, which can be discrete or continuous. Initially, the discrete variables of interest include indicators such as routing path selection and assignment. Besides, the specific continuous indicators are energy-efficiency optimization and load balancing with QoS guaranteed metrics, which are required to mitigate network congestion. Based on the work summarized in Table 9-15, the analysis reveals the extensive use of DQL and policy gradient approaches in addressing discrete and continuous control problem, in that respect.

c: SDN-BASED ML AND DL ROUTING OPTIMIZATION STUDIES AND CHALLENGES

In this part of the work, we focus on the use of SL and DRL. A main motivation for using ML techniques is due to their suitability to resolve complicated problems in typically complex networking field. The use of DRL emphasizes the training and learning of the target algorithmic models to determine the finest sequence of actions desired for maximizing the target reward. Specifically, the work focuses on energy-efficiency and routing optimization in SDN-enabled networks. Based on the above analysis and observation, we maintain the observation that the optimization of both energy-efficiency and routing are important functions SDN-enabled networks, this is because their metrics provide the much desired help to evaluation network performance. Based on the previous comparative analysis, a number of observations can be made, from which the following challenges are defined.

Challenges: Following are the challenges identified based on the analysis of current SDN-based ML and DL routing optimization studies:

(i) Performing precise hyper-parameter setting for DL networks can be difficult due to the dynamicity of the network environment, with time-varying network topology and traffic load.
(ii) Using supervised ML algorithmic framework when collecting the required adequate labelled training dataset incurs high computational overheads (complexity).

d: SDN-BASED ML AND DL QOS GUARANTEED STUDIES AND THE CHALLENGES

Unlike the above subsection which emphasizes on energy-efficiency and routing optimization functionalities, here we consider traffic prediction with all the important QoS guaranteed metrics in such SDN-enabled networks. The important QoS metrics include load balancing (to reduce traffic congestion), throughput, delay, jitter and packet loss. The emphasis in this work is on load balancing metric to reduce traffic congestion and improve network performance. As revealed earlier, the prediction of the QoS metrics commonly employed by operators and ISPs to evaluate network performance is an important consideration in similar communication networks. Using the summary provided in Table 13, selected SDN-based ML and DRL QoS prediction studies have been analyzed, upon which observations have been made and the following challenges are identified.

Challenges: A major research challenge of ML and DRL techniques in SDN involves the scarcity of labelled data required to train and learn the built DNN models. The difficulty to generate adequate labelled training dataset is due to high cost and time limitation. Normally, there is need for large volumes of training data, the scarcity of which can compromise the accuracy and choice of algorithmic frameworks. Also, the need for adequate training dataset can to a large extent determine the performance of supervised ML algorithmic frameworks, in terms of training and learning time taken to attain convergence.

Generally, a popular view shared by many researchers to provide working solutions is to consider the imperative strategy to integrate supervised, unsupervised and DRL to teach the constructed DNN on how to learn with limited data. On one hand, this strategy means that unsupervised and supervised learning can be based on limited data. On the other hand, DRL can be performed to teach the DNN on how to pool its knowledge to improve efficiency and effectiveness to learn new events. This strategy can minimise the amount of training data needed.

B. FUTURE RESEARCH DIRECTION

Based on the above observation and challenges, energy-efficient routing and load balancing with QoS guarantees are important TE objectives, especially in the realization of quality management and control of networks. On the one hand, the use of energy-efficient solutions in hybrid SDN/OSPF can potentially lead to OPEX reductions. On the other hand, load balancing with QoS guarantees can overcome network congestion and improve QoS and QoE in such networks. Additionally, it is important to observe that single or non-integrated implementation of all the QoS metrics can still result in network performance degradation in such hybrid SDN/OSPF. Therefore, to provide additional gain, the work herein recommends further research to devise innovative solutions that can achieve a good trade-off between energy-efficient routing and performance optimization.

Additionally, with current advances in communication networks, the need to resolve the challenge of insufficient data and embrace of traffic prediction have become important requirements for communications service providers to deliver the required QoT, more so in the perspective of the emerging high volume multimedia services or applications. Essentially, traffic prediction enables network state to be estimated, hence resolving routing issues such as congestion well ahead before QoS can be compromised. This condition can be resolved by leveraging the availability of data, and the potential application of RNN in traffic prediction analysis to derive accurate energy-efficient routing decision outcomes. Today, many researchers envision that a promising solution to the current challenges involves combining SDN and ML-driven network analytics, thus embracing AI approaches in the operational management and control of networks.

Motivated by the current advances in networks, combined embrace of ML, AI and big data analytics in the context of SDN-enabled networks can improve the capabilities of traditional IP-based networks. This strategy facilitates the delivery of scalable and responsive multimedia services in an energy-efficient way, especially in the emerging dynamic large-sized networks. To this end, this work recommends future studies to leverage conjoint ML and AI-assisted predictive and rate adaptive data-driven energy-efficient routing approaches that employ RNN and linear regression technique in hybrid SDN/OSPF networks. This will provide the option to extend programmability to the core domain in existing telecommunications networks, with the deployment of hybrid SDN/OSPF networks. In light of this strategy, networks can potentially deliver the goal of achieving dynamic and globally cost-effective energy-efficient routing of traffic flows to balance the load and prioritising end-to-end QoS guaranteed multimedia applications hybrid SDN/OSPF networks.

In the current state of network evolution characterized by the ever-increasing volumes of traffic flows, QoS guaranteed restrictions and differentiated service provisioning and the demand for energy-efficient greener networks that feature reductions in CAPEX and OPEX, it is important for the Telecommunication industry to embrace a network management and control framework that leverages ML and DRL approaches to achieve predictive and rate adaptive traffic prediction and energy-efficient routing to balance the load in transitional hybrid SDN/OSPF network.

Summary: The aforementioned section has presented the related challenges and future research direction based on the evaluation conducted. Moving forward, it is essential to devise practical solutions. We believe the discussions provided in this part of the work will unveil new research spaces for advancement toward the much desired intelligent next generation networks.

VII. PROPOSED ML AND DRL FRAMEWORK

This section considers the proposed integrated SDN-enabled ML and DRL-based architectural framework. The various subsections covered include overview of the proposed framework, description of the proposed ML and DRL framework, system architecture, conceptual framework, LSTM-RNN network architecture and the generic DRL architecture.

Basically, the article considers a hybrid SDN/OSPF network deployment, where the SDN controller which forms the main node in the network performs energy-efficient routing and performance with QoS guarantees. Moreover, it performs traffic flow routing decisions that interlink the various network sub-domains in the hybrid network.

A. OVERVIEW OF THE PROPOSED FRAMEWORK

The current surge in data volumes has led to explosive Internet growth, advent of cloud computing and rapid progress in wireless communications [1]. There are two important concerns that arise in the current state of network expansion. First, communications service providers need to deploy efficient and intelligent networking solutions to support the huge traffic demands and to reduce the capacity pressure on their network infrastructure. Second, novel energy-efficient networks should be devised to reduce network utility costs and carbon footprint. Because complete SDN deployment is currently impractical in the short-term, hybrid SDN/OSPF becomes the preferred alternative for MNOs and ISPs, however, it suffers various challenges [52]–[56], [58], [62]–[64], [66]. Although many model-driven energy-efficient routing and load balancing algorithms exist for use in hybrid SDN/OSPF, they are barely generic and reactive by design and are characterized by the manual control plane forwarding configuration mechanisms. Given the above, these solutions can still leads to performance degradation, in modern large-sized dynamic networks [52], [67], [68], [104], [135], [142].

The recent technological breakthroughs in ML and DL has significantly influenced the innovative efforts of researchers, an aspect that is hard to ignore. This trend has led to diverse subdivisions of networking developments. Today, a popular network design trend among communications network researchers and operators indicate a progressive transition from network-driven models that consider QoS metrics to model-free data-driven strategies [24], [104]. Besides, the recent progress in ML techniques such as RNN and DRL has surpassed human level performance in addressing extensive online network control and management tasks [25]–[28]. This has motivated the need to employ innovative model-free data-driven frameworks that consider cost-effective energy-efficient routing and performance optimization with QoS guarantees, in hybrid SDN/OSPF. We envision that the solution to the problematic trade-off between energy-efficient routing and network performance will greatly depend on the most promising data-driven ML and DRL approaches [24], [129], [104]. To illustrate the above relationship, the next subsection considers a description of the proposed supervised ML and DRL for Hybrid SDN/OSPF.

B. DESCRIPTION OF THE SUPERVISED ML AND DRL FRAMEWORK

Existing solutions to energy-efficient routing are rule-based HA, which are easier to interpret and implement. However, in the current state of network expansion, such solutions are inadequate given the generic nature of model design [73], [143]. Differently, this work for the first time, to the best of our knowledge proposes a novel architectural framework which leverages an integrated supervised ML and DRL techniques in hybrid SDN/OSPF networks to realise rate adaptive and cost-effective energy-efficient routing and performance optimization with QoS guarantees, to distribute a diversity of modern multimedia services or applications [98], [99], [104], [105], [109], [113], [115], [117], [123], [129], [134], [137], [144].

The proposed framework is composed of a hybrid SDN-enabled supervised ML module and DRL module. On the one hand, the hybrid SDN-enabled supervised ML module is divided into three phases which include feature extraction, deployment (algorithmic model training and testing), and result and analysis or evaluation. By and large, the module is based on a DNN construction which employs LSTM-RNN algorithmic technique to perform traffic flow prediction using time-series dataset [108]. Based on the supervised ML module, LSTM-RNN algorithm is employed to extract short-term network data traffic variabilities and periodicities, resulting in the meaningful features which are combined at the integration step to ensure traffic flow prediction and energy-efficient routing with guaranteed QoS performance. On the other hand, the DRL module performs learning from the existing historical data or right from scratch by iteratively interfacing with the defined network setting [113]–[117], [129]. Using publicly available dataset, the module can be evaluated in terms of accuracy and convergence speed.

The DRL module is employed to ensure energy-efficiency and network performance by interfacing with the network setting. This explains the rationale of how the module is able to learn from scratch or by relying on the supervised module. This form an integrated solution which leverages LSTM-RNN network architecture and DRL technique to achieve traffic prediction and rate adaptive energy-efficient routing and performance optimization with guaranteed QoS provisioning, in hybrid SDN/OSPF.

Unlike traditional NN approaches, which directly employ shallow LSTM-RNN [114], [116], the proposed solution employs Deep LSTM-RNN [109], [129]. Recently, LSTM-RNN architecture has drawn the interest of researchers. Through leverage of the interfacing strategy, we can resolve the issue of network traffic load variability and status changes. The DRL module aims to alleviate the energy-efficient routing problem by exploiting the pinning control theory [119]. Moreover, we integrate the pinning control theory with the DRL module to manage the hybrid network.

Unlike the existing ML solutions, the proposed framework addresses several objectives using several algorithmic frameworks. The objectives addressed include energy-saving efficiency, network performance enhancement, computational efficiency (which features speed and memory space utilization) and dynamicity, particularly in modern large-sized networks with time-varying and growing volumes of heavy multimedia traffic. Clearly, there is hardly any report about the application of LSTM-RNN technique for network traffic flow prediction and the optimisation of energy-efficient routing in hybrid SDN/OSPF. Given the promise, more research effort is required.

Moreover, the DRL module is designed to employ deep Q-learning and SARSA algorithms to train the optimal policy in hybrid SDN/OSPF networks [105], [113], [106]–[117], [126], [130], [139], [144]. Lately, DRL algorithms such as DQL and SARSA have gained the interest of researchers as suitable options to resolve the issue of exploding state space action in traditional RL architectures [141]. DRL algorithmic techniques can deliver such benefits at reduced training time and memory requirement.

Also, different from traditional DRL architectures which rely on the limited table-based agents to perform on a specific observed network topology during training, the techniques of DQL performs better over unfamiliar network topologies to successfully ensure policy generalization [109]. The basis of this is that computer-based networks are primarily represented as graphs. To this effect, there is need to devise solutions to tackle the above problem.

Lastly, the general issue of the lack of adequate data can be resolved. The aim of the proposed approach is to leverage and enhance shallow RNN predictive multi-step ahead approach employed by the authors [99], for application in the proposed integrated GA-LSTM-RNN network architecture and DQL technique. This can potentially achieve predictive optimization of link rates for energy-efficiency and performance, by traffic demand forecasting, in hybrid SDN/OSPF. Regarding the issue of parameter setting, given the dynamicity of network topology and traffic load, this work intends to employ the increasingly popular GA in LSTM-RNN [116].

C. SYSTEM ARCHITECTURE

This subsection describes the general hybrid SDN/OSPF architectural framework. The general idea covered include the types of hybrid network architectures considered, basic concepts of hybrid SDN/OSPF, hybrid SDN/OSPF routing mechanism and the functional components. Provided in Fig. 6 is a representation of the proposed framework. Basically, the framework consists of four (4) planes to be discussed later in this subsection.

1) HYBRID SDN/OSPF NETWORK ARCHITECTURES

As stated in Section II, based on the use of the pinning control theory [42], the framework is intended to leverage the functionality of SDN, by using SDN-enabled nodes to assign data traffic to multiple next-hops. The framework features two key hybrid network architectures required to guide network deployment. First, we employ the SDN and Non-SDN architecture to guide planned deployment of hybrid SDN switches in legacy networks [19], [50], [141]. Moreover, the SDN switches are deployed among legacy nodes a result of which is hybrid SDN/OSPF network construction. Second, we consider the upgrade/agent architectural design in which the cooperation between the distributed and the centralized routing control plane is achieved using shim hardware, which are hybrid switches or software components deployed and configured in existing legacy networks [142]. We particularly consider these two architectures to overcome the limitations pertaining to embracing ML and DRL in hybrid SDN/OSPF networks. First and foremost, we consider the monitoring overhead as a major hindrance to data collection from the limited number of sources in such hybrid SDN-enabled network [146]. Secondly, is the automation difficulty in ML, brought about by the heterogeneity nature of such hybrid SDN/OSPF networks [147]. Heterogeneity can limit the degree of SDN control over legacy devices and this discourages the embrace of ML and DRL. Our design considers strategic deployment of nodes to overcome such limitations.

2) BASIC CONCEPTS OF HYBRID SDN/OSPF

Principally, this work considers a hybrid system architecture that is based on the flow route scheme proposed in [63]. The flow route network scheme can support the integration of SDN-enabled devices into existing legacy IP-based networks. Moreover, the scheme considers a data forwarding plane that is composed of legacy IP routers and SDN-enabled switches. Besides, the need to differentiate between legacy IP routers and SDN-enabled switches is met through the capability of the target device in providing SDN protocol support. Since SDN-enabled switches are placed under the control of the SDN controller, the computation of the forwarding flow table of such SDN-enabled switches is performed by the controller device. Additionally, the IP-based routers employ conventional hop-by-hop routing protocols such as RIP and OSPF to forward data packets.

As shown in Fig. 6, we consider a system architecture consisting of a supervised ML and a DRL framework, whose focus is the attainment of energy-efficient routing and QoS guaranteed performance. By composition, the architecture is divided into four planes, including the physical plane, datalink plane, control plane and artificial intelligence (AI) control plane. Given this composition, we aim to leverage SDN capabilities to provide different benefits that may include: global visibility feature to efficiently collect data, to support the use of ML and DRL algorithms [67]; data analysis and network optimization techniques can be exploited to support intelligence network decision-making [67], [148]; network programmability leading to real-time optimization of network routing solutions based on resource allocation and data traffic configuration [149]. Precisely, the SDN controller is intended to perform near-real-time updates on the

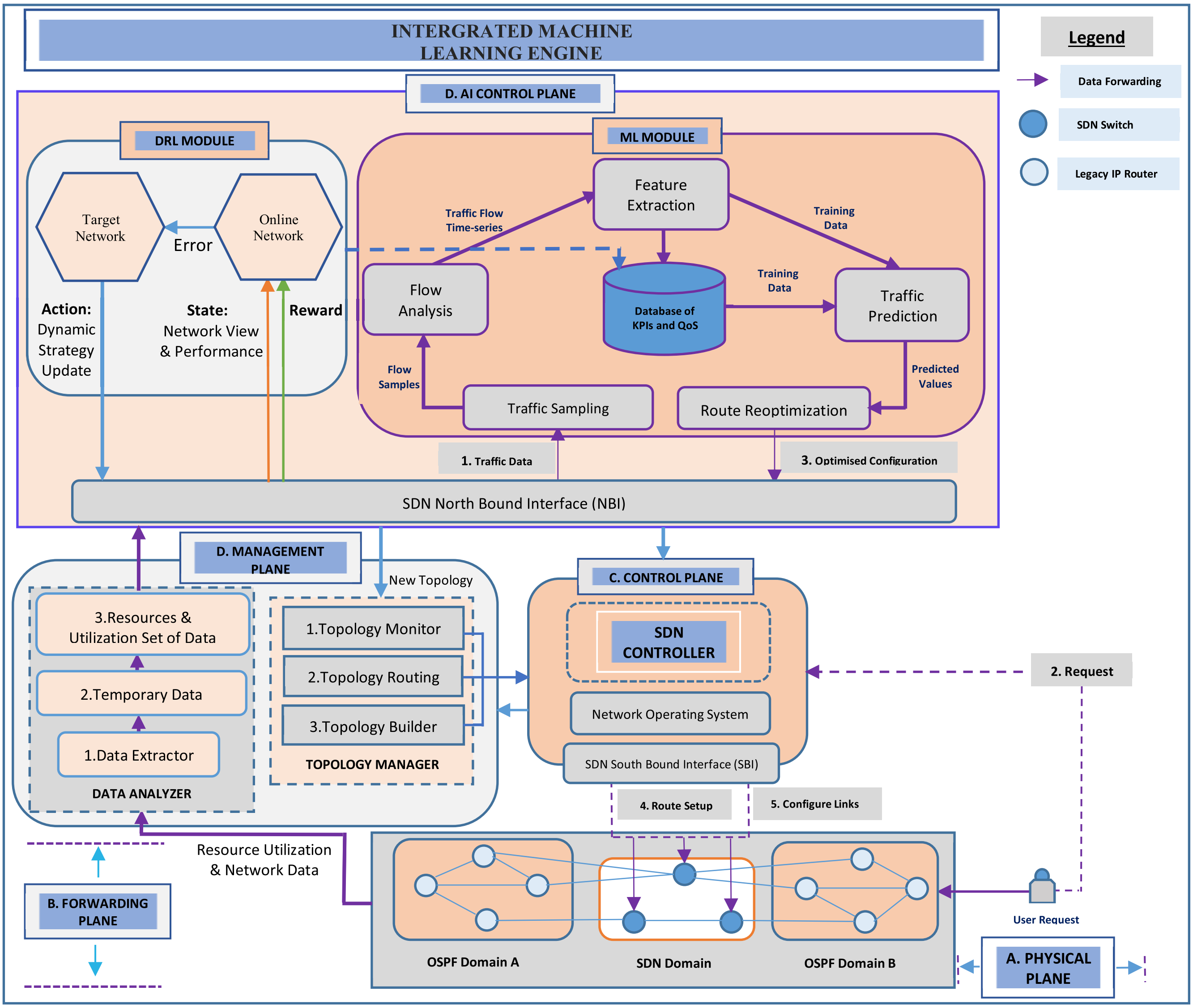

FIGURE 6. System architecture of the proposed supervised ML and DRL framework in the scope of network traffic prediction, energy-efficient routing and performance in hybrid SDN/OSPF networks.

energy-efficient routing optimization policy, to dynamically perform traffic forwarding. In the rest of this subsection, we discuss the aforementioned architectural planes.

a: PHYSICAL PLANE

By considering Fig 6 in the bottom-up direction, the first layer is the physical plane which consists of various transactions originating from terminals such as laptops or smartphones [148]. These devices are connected to the network switches or service gateways through wireline or wireless communications devices. The service gateway connects with Internet based routers or SDN-enabled routers in the data plane. In some classical SDN-based architecture, these physical plane devices are considered to be under the forwarding plane. For clarity, this work separates the forwarding devices from the data originating or sourcing devices [56].

b: DATA PLANE

The data plane is constructed upon hybrid SDN/OSPF networks and it is composed of forwarding devices such as legacy IP routers and SDN enabled switches [114], [150]. On the one hand, the programmable SDN-enabled forwarding switches can be employed to execute flexible network flow forwarding policies. They are equally useful for the process of network status information gathering. These switches hold the capacity to ensure more granularity for network administrators to deal with traffic classification and scheduling. Besides, every flow entry contains a counter field to define each flow intensity. All these details can help to show the network traffic distribution. Such programmable devices can be used to support online updates of rules that guide flow forwarding in the network. On the other hand, traditional non-programmable devices such as IP routers lack the required flexibility and must rely on SDN-enabled devices to capture existing legacy sub-domains [50], [51]. This configuration allows the SDN controller to perform near-real-time updates on the routing optimization policy, to dynamically adjust the network state. This data plane is basically structured into sub-domains which are linked through strategically located SDN-enabled switches [44], [151]. The partitioning of OSPF network into sub-domains can promote TE through advancing control over the interconnecting sub-domain routers. In the context of legacy IP-based routers, the SDN switches are viewed as common IP routers.

c: CONTROL PLANE

The control plane is constructed based on standard SDN network model and it is connected to the data plane through the south bound interface (SBI) and the management plane through the NBI. Basically, the control plane houses the SDN controller device which is connected to the SDN switches through the SBI with the help of an OpenFlow protocol. Using the SBI, the SDN controller can capture the network state information like flow table statistics, include network resources availability and utilization levels, among others [126], [150]. This information supports the execution of control policies based on an extensive network construction. In addition, the SDN controller acquires the QoS parameter measurement information which is used for estimation by current network approaches. Next, the controller generates fine-grained energy-efficient routing policies, which can alternatively be converted into flow tables and hence deployed on the target SDN switches. This is accomplished through the services of the SBI. Finally, the SDN controller employs the support of the NBI services to relay the global network view which is precisely the input state to the management plane, to ultimately access dynamic decision policy [126].

d: MANAGEMENT PLANE

The management, which is comparable to the application plane in traditional SDN, is concerned with ensuring the accurate network operation and performance in the long-term. The management plane characterizes and configures the network topology [152]. It is responsible for the collecting telemetry information at the data plane while maintaining a historical record of the state of the network and events. The management plane also handles network monitoring functionality to provide vital network analytics. To perform this task, the management plane uses the topology data analyzer and the topology manager as illustrated in Fig. 6. The data analyzer collects traffic flow and resource utilization data from the forwarding plane devices. Besides, the topology manager performs topology monitoring, topology routing computation and topology building. During network execution, the management plane performs the collection of aggregated and network topology utilization data, destined for the AI control plane. Subsequently, the management plane receives the required feedback from the AI control plane to support topology construction, topology-based route calculation and topology monitoring (sensing).

e: AI CONTROL PLANE

The AI control plane is the main part of the framework, commonly comparable to the human brain, by functionality. Generally, we consider an AI control plane that leverages the network links and node utilization details, using an agent-based data collection element to generate huge quantities of resource consumption data to realize a self-driven network. As illustrated in Fig. 6, the AI plane interacts with the SDN-based application plane to fetch the aggregated data generated by the SDN controller and other applications.

One major aspect that is central to the AI control plane is its capability to combine behavioural algorithmic models with reasoning techniques that are concerned with decision-making in SDN-enabled networks [151], [152]. The AI control plane can leverage the capabilities of the control plane and management plane to gain rich network visibility and intelligent network decision-making. It is charged with the role of learning network behaviour and performing automated network operations.

Primarily, the AI control plane handles the processing of network data analytics generated by the management plane using various data analysis and network optimization techniques. It then transforms these into knowledge using ML algorithmic techniques. Finally, such knowledge is employed for network decision-making. The AI control plane of the network can potentially recommend specific configurations without the intervention of the human operator. The SDN-enabled network controller can then regulate the traffic flows in the data plane, based on the decisions assumed [67], [148]. Although it is a slow process to represent and learn from this information, the automated use of such knowledge can be done at a time-scale closer to the control plane and management plane time scale. An important component within the AI control plane, that is worth mentioning is the machine learning engine (ML engine).

ML Engine: This represents an adaptive software glued on top of the AI control plane, and is dedicated to the goal of providing dynamic requirements to support fined-grained adaptation to the observed network environment, rather than the execution of static hard coded network-based behaviour. The use of ML engine can ensure the much desired response capability to unforeseen system conditions in emerging communication networks. By composition, the ML engine pools together and provides access to a range of ML techniques designed to perform adaptations at execution time. In SDN-enabled networks, we can leverage the network-wide view and current state of network performance, and then provide this as input information to intelligent algorithmic techniques [126].

By functionality, the ML engine is responsible for the overall data pre-processing, offline and online training, and modelling. The outcome of these functions is a robust prediction model for traffic demand prediction. This model is employed to direct the control plane by providing the resultant command to the centralized SDN controller in hybrid SDN/OSPF networks. Normally, the ML engine performs important tasks such as generation of an optimized subgraph using the forwarded state of the network and topology information. The output of the ML engine includes the link weights for all the links in the network topology. The weights are useful in the implementation of actual energy-efficient routing plan updates in the target network. In the case of RL, each time the ML engine interacts with the hybrid SDN network, an energy-efficient routing plan is generated and hence evaluated in terms of policy performance, given the reward. The reward can be validated by the service quality measured using QoS metrics, which are captured from the deployed network. Afterword, the ML engine updates the algorithmic parameters in an effort to achieve a better reward. After training the neural network for a defined time frame, the ML engine acquires adequate experience, through the interaction with the network environment. Ultimately, the ML engine can generate near-optimal energy-efficient routing plan for the target network deployment [126].

3) HYBRID SDN/OSPF ROUTING MECHANISM

In legacy IP-based networks, energy-efficient routing is performed by the IP routers using the traffic destination address and the most suitable route. When a data packet arrives at a router, it is sent to one of the router ports, based on the packets destination address and the information in the routing table. For such legacy IP networks, each router deployed in the network finalizes its routing table using such network routing protocol, like RIP and OSPF. The protocol in use determines the most suitable route using the computed cost of the route. Moreover, routing protocols transfer advertisement packets that contain the routing information of the sender. Every IP router in the network finalizes its respective routing table by employing packet advertisement from the neighbouring routers.

Different from legacy IP networks, SDN-based routing is accomplished by receiving a new flow arrival at the ingress OpenFlow switch, whose first packet is extracted and then sent to the SDN controller device. The SDN controller then selects the best suited route based on the network topology information, link states, as well as other necessary policies and decision criteria. Second, the SDN device does the configuration of the OpenFlow switches in the selected routes to perform traffic forwarding accordingly.

In the perspective of hybrid SDN/OSPF, legacy IP routers view the SDN-enabled switches as ordinary IP routers. Thus, when computing the traffic flow forwarding paths, legacy IP routers, the existence of SDN-enabled switches allows external transparency to the rest of the IP routers [37], [38]. Therefore, SDN-enabled switches in the hybrid SDN/OSPF network provide global traffic forwarding to both SDN-enabled switches and legacy IP switches.

Moreover, legacy IP routers implement the OSPF protocol, in addition to establishing adjacent relations with each other through transmission of the Hello message, and then exchange network topology information, such as link weights by using the link state advertisement (LSA) message, then update the link state database (LSD) [63], which stores the global network topology information. Lastly, each IP router stores the duplicate LSP, computes the shortest path trees (SPTs) to setup a routing table and forwarding information base (FIB), centered on LSD.

In the short-term, SDN-enabled switches direct the network-based topology information to the centralized SDN controller. In this state, the SDN controller has up-to-date knowledge about the OSPF link weights and the traffic load on each link. Observe that a given SDN-enabled switch can have several next-hops to the destination node. Yet, an ordinary IP-based router can have a single feasible path to the destination node, when equal cost multiple path (ECMP) is employed.

Besides, an SDN-enabled switch can have multiple paths to the outgoing links, given the SDN-enabled switch. While the IP router can only execute the OSPF routing protocol, the SDN-enabled switch can operate in two different modes, namely, OSPF mode and hybrid mode [63]. In the OSPF operational mode, the SDN-enabled switch performs like a OSPF switch. In the hybrid operational mode, the switch forwards traffic flows in accordance with the guiding rules in the flow entries setup at the SDN controller.

Additionally, the delivery of application-driven QoS guaranteed routing forwarding in such hybrid networks, demand for the design of an intelligent or smart traffic forwarding plan, to perform flexible network resource allocation and traffic routing decisions under the defined structure [123], [129]. This aims to improve the network resource utilization efficiency and QoS guarantees for the desired services or applications.

4) FUNCTIONAL COMPONENTS OF THE ARCHITECTURE

Generally, based on Fig. 6, the proposed system architecture can be described in the perspective of functionality. There are three functional components that constitute the entire architecture: the data analyzer, the topology monitor and machine learning engine. Provided below is a brief description of each of these three components:

a: DATA ANALYZER

The data analyzer also called data analytics platform is an important component that is located within the control plane [152]. The data analyzer is concerned with the monitoring the network traffic information, and the archival of forwarded traffic information generated by active applications. Such traffic information includes origin-destination pairs, traffic data rates, traffic demand arrival time and flow amounts. To perform the above tasks, the data analyzer relies on the services provided by the SDN controller splice, as discussed next.

The data analyzer contains the supervisor agent and the client agent, which are two important agent-based units responsible for collecting data traffic flow information from the forwarding plane and temporary storage in the data buffer [152]. Then, the temporary data are filtered to eliminate redundancies and stored in the TE database (TED). This dataset is forwarded to the DRL module, within the AI control plane for performance monitoring and network optimization. Recall that the focus is optimizing energy efficiency and performance with QoS guarantees.

b: TOPOLOGY MANAGER

The topology manager is concerned with the execution of traffic forwarding scheme. As shown in Fig 6, the three building units of the topology manager include topology monitor, topology routing calculator and the topology builder [152] perform topology monitoring, topology routing computation and topology building respectively. During run time, the management plane collects aggregated and resource utilization data, which is destined for the AI control plane. Then, the management plane receives the required feedback from the AI control plane to support topology construction, traffic routing computation and topology monitoring/sensing. Generally, the above starts with the implementation of topology discovery procedure whose role is to discover the structure of the network that either includes SDN switches or OSPF routers. The discovery of network topology starts when the supervisor and the client agents are employed to capture the network information regarding the current network, specifically the link state information and path state information [55]. Next, the QoS metric monitoring procedure in the control plane comes into play to quantity and compute specific network performance metrics. As mentioned earlier, such metrics may include traffic and packet load rates for each link and link delay. Upon obtaining this information, the SDN controller executes the path computation procedure to compute the path for energy-aware traffic forwarding.

To achieve network topology discovery, the topology manager relies on the controller, which initially monitors the network topology. Besides managing the capture of information regarding network organization and status of the network elements, the topology manager also handles the storage of cost-driven information on network links and forwarding switches. In case an element flops or goes out of service, the topology manager performs an update on the global topology information stored in a database [56]. The database in this case keeps track of connection maps of the underlying SDN switches and legacy IP routers as well as information concerning the path established between each ingress-egress pairs. The path state information is an abstraction of the physical network. It is upon this that the controller manages the abstract network maintained in the TED database. This work considers a novel topology discovery mechanism in which the centralized SDN controller has visibility of network switches using the Open Flow protocol, in addition to feasible view of legacy OSPF routers [148].

c: THE ML ENGINE

The ML engine represents an adaptive software glued on top of the AI plane for dynamic fined-grained adaptation to the observed network environment state. The ML engine is employed in the novel joint supervised ML and unsupervised DRL system. The focus is to perform learning of adaptive behaviours and package them into a reusable suit of ML algorithmic-driven adaptations. Besides, it is intended to support various use case scenarios that require training of the algorithmic models, without degrading end-to-end performance workload. Also, it required to generate an optimized subgraph by using the traffic load by performing learning operation on the available historical data. Then, the network state and topology information is forwarded to the ML engine. Given the dynamic capability of the module, limited traffic demands can result in a subgraph with a small traffic load of active network links as opposed to a subgraph with huge traffic load. The following section gives a description of the conceptual framework of the proposed ML and DRL system.

D. CONCEPTUAL FRAMEWORK OF THE SYSTE

This subsection gives an overview and a description of the methodology pertaining to the use of the proposed supervised ML & DRL framework.

1) OVERVIEW

The supervised ML & DRL architectural framework employs three different algorithms, which are categorized into supervised ML module or RL module. On the one hand, the data pre-processing algorithm and the refine algorithms are part of supervised ML module. The data pre-processing algorithms include principal component analysis (PCS) [153], [154] and correlation matrix (CM). Moreover, unlike problem-specific HA, the refine algorithms (meta-heuristics) are meant to solve general-purpose difficult optimization problems which are hard for deterministic techniques to solve in a reasonable time. These algorithms include GA and HA. On the other hand, the Q-routing algorithm belongs to and is employed by the DRL module.

Provided in Fig. 7 is an illustration of the framework. As revealed in the figure, the proposed framework is structured into three (3) phases and these include data collection, pre-processing and deployment. Moreover, by using the framework, the SDN controller is employed to perform traffic monitoring. After performing traffic analysis using the observed data, feature vectors are extracted and stored in the database. Then, the historical data contained in the database is employed to initialise and train the traffic predictor. Subsequently, the traffic predictor performs the estimation of future steps of traffic, based on the new sample. Also, the predictor result is employed in the optimization step to compute the optimal path required to route traffic flows.

Prior to execution of the framework, the choice of whether to begin with the supervised ML module or unsupervised

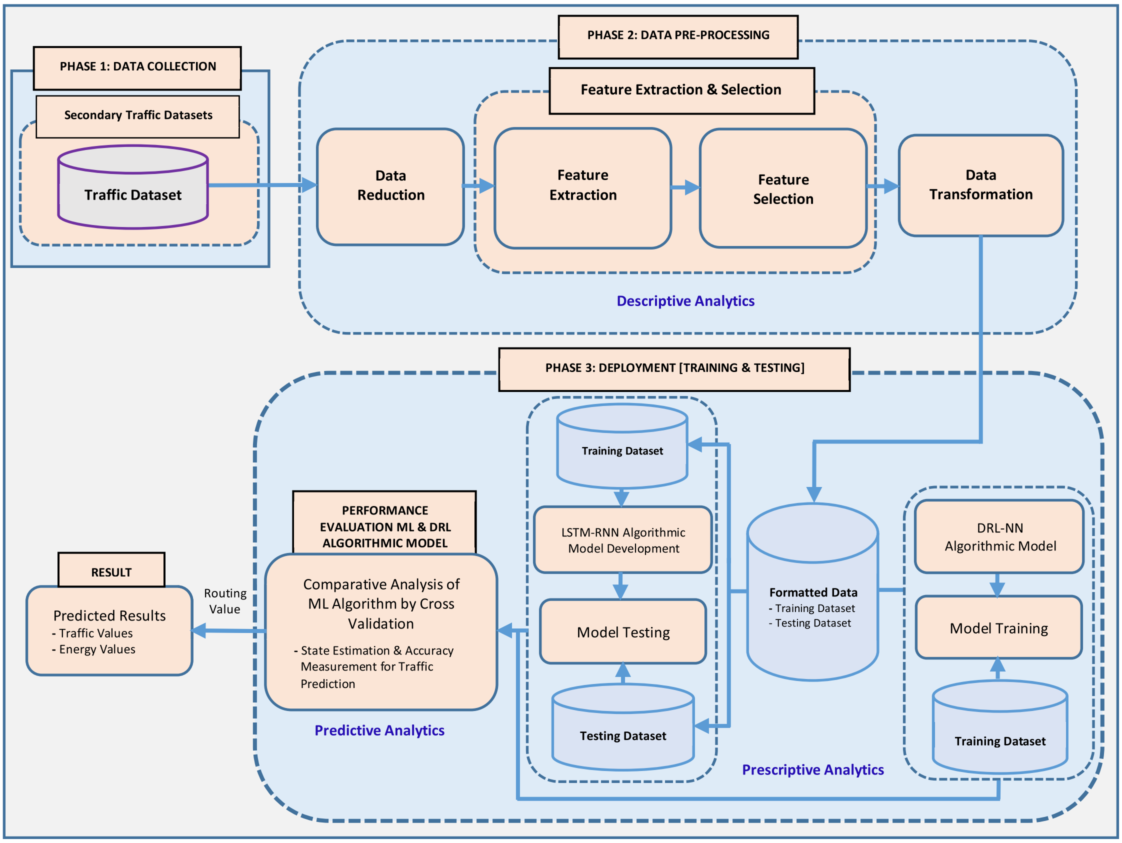

FIGURE 7. **Conceptual diagram of the proposed supervised ML and DRL framework for network traffic prediction, energy-efficient routing and performance enhancement in hybrid SDN/OSPF networks.**

DRL module must made. Essentially, choice of the initial algorithm for execution depends on the availability of historical data. Assuming historical data is available, the ML engine directs control to supervised ML algorithmic, making it the target execution module

2) METHODOLOGY

As illustrated in Fig. 7, the methodology is made up of a number of phases required to develop the proposed ML & DRL framework, and hence build traffic flow predictor model and energy-efficient model. The objective is to achieve traffic prediction, energy-efficient routing optimization, with QoS-based performance guarantees. Subsequently, based on the availability of historical data, we give a detained discussion of the methodology from the two perspectives: Supervised ML module and Unsupervised DRL module.

a: SUPERVISED ML MODULE

This part of the methodology is divided into three phases that include data collection, data pre-processing and deployment, a description of which is given in the rest of the part.

Phase 1 (Data Collection): Data collection element represents a procedure whose main focus is performing traffic sampling and flow analysis roles. Basically, the traffic sampling unit of the data collection element employs the traffic flow. The sampling and flow analysis is performed by tools such as IPFIX (RFC 7011), NetFlow (RFC 3954) and NETCONFIG (RFC 6241) in SDN-enabled environment. SDN controller services to perform network monitoring and collection of current traffic samples (statistics) from each The captured samples include traffic rates from the target network topology. These samples are collected over a defined time frame of one minute, one hour, one day, one week, among others time scales. The data is collected in the short-term and long-term nature.

The definition of traffic flows depends on the kind network under consideration. For instance, in an IP network we can define a set of all data packets with the same protocol type to be characterised by: source IP address, destination IP address, source port, destination port, packet direction (uplink or downlink data rates), bytes in payload, inter-arrival time and window size. All these belong to the same traffic flow. Moreover, the collected network flow samples feature both the uplink and downlink network data rate scenarios. The monitoring should be directed to large traffic flows, because given the huge volumes of traffic flows, it is appropriate to ensure better optimization of energy use in communication networks. So, to meet this condition, monitoring effort should be selectively directed to large traffic flows as opposed to mice flows. Ultimately, the output of the data collection phase are the traffic samples or rates which is store in a database. Such sampled output provides the required input for the data pre-processing phase.

Phase 2 (Data Pre-Processing): Data prep-processing is responsible for mining of daily periodical variabilities from the observed data traffic samples. The goal is to sieve out short-term network traffic variabilities which is difficult to predict. This sort of data pre-processing action is aimed at improving the degree of accuracy of the long-term variations.

Practically, the data pre-processing element represents ML algorithmic techniques concerned with the transformation of the collected data samples into the desired format. These algorithms are dedicated to performing two key processes that include feature representation and feature dimension reduction. These steps can be performed through deployment of approaches such as PCA or CM. The selected approaches must be used with care to generate related features required to support model construction requirement. Based on the use of these techniques, the generated feature subsets are then used to construct the traffic prediction model and energy-efficient model. This work considers the use of CM approach for data pre-processing.

Additionally, as revealed in the figure, the pre-processing element is divided into two algorithmic techniques: flow analysis and feature selection. Moreover, the execution of data pre-processing element begins when the supervised ML module employs the preferred approach to perform the desired tasks. This work considers the use of RNN regression method for model construction. The purposed is to construct an effective traffic prediction and rate adaptive energy-efficient routing model characterised by high accuracy, generality and scalability.

Lastly, the accuracy of the energy-efficient routing model is evaluated to determine the effectiveness. In this part of the work, we describe the pre-processing process that is structured into the following sub-parts:

i) Flow Analysis: Flow analysis is a process which employs the pre-processing algorithm on the collected data samples to derive traffic patterns or trends, based on the use of time-series analysis. When performing flow analysis, a number of key considerations should be taken into account. First, the performance of the desired supervised ML algorithmic network model depends on the selection of relevant features. Second, complex traffic features require additional memory, computational power and a lengthy time to do training. Third, the ML algorithm can over-fit the training dataset and can suffer poor generalization for unseen data. Finally, the successful execution of flow analysis process outputs time-series traffic patterns, useful as input in the feature extraction stage.

ii) Feature Extraction: Feature extraction is a process concerned with the extraction of important features required to construct a proper ML network model. Such model construction demands for the inclusion of the desired parameters. It refers to a procedure performed by an algorithmic to extract a sub-set of important features in the existing time-series dataset. The extracted features must be relevant to the identification of interesting patterns. The output of feature extraction is the various generated candidate feature sub-sets.

iii) Feature Dimension Reduction: Feature dimension reduction is a procedure performed by an algorithmic technique to eliminate duplicated entries in the collected data samples. Performing feature dimension reduction process is essential because the existence of duplicated data samples can significantly compromise the performance and accuracy of the supervised ML network model.

iv) Feature Selection: The next procedure after feature dimension reduction id feature selection. Feature selection represents a ML procedure performed by the selection algorithmic techniques, to extract a sub-set of important features in the traffic time-series dataset. The determination of feature sub-sets can be performed by such algorithms as CA (correlation based filter technique) or PCA (wrapper technique). Moreover, the features extracted must be relevant to the identification of interesting patterns.

v) Data Transformation: After performing data extraction and selection, data transformation follows. Data transformation involves the conversion of the feature sub-sets into the right format, in readiness for model training and testing. A commonly used data file conversion format with a wide range of modelling libraries is the comma separated (.CSV) file format. Besides, data transformation includes conversion from symbolic to numeric and parsing of data. Moreover, it features the separation of training and test datasets, in preparation for the ML network model training and testing runs, all of which are performed at the deployment phase.

Phase 3 (Deployment): The deployment phase is the final phase of the proposed methodology. Primarily, the deployment phase is divided into performance evaluation, and result and analysis.

i) Performance Evaluation: This is a process of the supervised ML & DRL algorithmic framework concerned with the definition of the configuration settings and construction of traffic prediction model and the energy-efficient routing model. In this work, we divide performance evaluation into two: Traffic Prediction Modelling and Energy-Efficient Routing Modelling.

Step 1 (Prediction Modelling): This work employs multi-step-ahead prediction algorithmic model suggested in [104], to predict future traffic demands, to be employed to perform routing re-configuration. A major idea underlying this prediction algorithm is the multi-scale dynamic behaviour of data traffic flows. Different from other time-series prediction algorithmic models, the design of multi-step ahead prediction algorithmic model is based on traffic characteristics. The prediction algorithm uses traffic flow information from diverse time-scales in order to limit the propagation of errors.

Basically, the algorithm performs two specific steps: first, it predicts traffic flows based on diverse time scales; second, these various traffic flow prediction output are combined to ultimately predict future traffic demands. Therefore, to construct a suitable traffic prediction model, the prediction algorithm employs the subset of feature vectors from the previous phase on a deep neural network (DNN) regression-based method.

Hyperparameter Tuning: To perform RNN model training and testing, and construct a neural network model for traffic prediction, it is important to first perform hyperparameter tuning. However, configuration of hyperparameters represents one of the most daunting tasks. Hyperparameters refer to the variables that determine the structure (for instance, the number of hidden units) and the variables that will be used to determine the method of training (for instance, the learning rate and number of iterations) the RNN-LSTM network architecture. Observe that the hyperparameters ought to be set before training (before link such RNN-LSTM network architecture is complicated.

Precisely, the RNN-LSTM network model is employed in combination with the representative hyperparameters and the TensorFlow library to construct the prediction model. In terms of application, the proposed ML framework is not restricted to a specific prediction algorithmic technique. So, it can be employed in combination with other prediction algorithms such as ARIMA, FARIMA, BPNN. To develop the prediction model, we perform two principle processes, that include hyperparameter tuning and RNN Model Training and Testing. Provided in Fig. 8 is an illustration of the sequential training, testing and validation process of the DRL module.

RNN-LSTM Network Traffic Prediction Model Training: This is concerned with extra training and tuning of the RNN-LSTM network traffic prediction model in an iterative run to fine-tune the hyperparameters. We consider the concept of hyperparameter optimisation (HPO). The HPO concept represents a mechanism employed to routinely explore the search space of prospective hyperparameters, build a sequence of RNN-LSTM network models, and hence perform RNN-LSTM network model comparison based on the appropriate metrics optimization (HPO), which is a concept required for fine-tuning. The application of HPO demands the specification of a wide-range of values, meant to explore the respective hyperparameters. Typically, this is made up of training specifications in the scale of tenth to hundreds.

RNN-LSTM Network Traffic Prediction Model Testing & Validation: During model testing, validation check is an important task, mainly concerned with justification of the performance or accuracy of the trained RNN-LSTM network traffic prediction model, as compared against the validation data set. Testing means the application of the trained prediction model to predict the unknown future traffic demands. We use cross-validation technique to select the right parameter k in an n-fold cross validation [137]. To perform model testing, the RNN-LSTM network traffic prediction model is checked based on a subset of features. Moreover, we employ RNN regression-based method to develop an RNN-LSTM network traffic prediction model. To increase the model accuracy, refining algorithm is applied. Assuming the generated RNN-LSTM network traffic prediction model is acceptable in terms of accuracy, an advanced step is taken to build the inference RNN-LSTM network traffic prediction model. The built RNN-LSTM network traffic prediction model is used to predict the new traffic flow values. Assuming the results are insufficient, the process is repeated, let alone perform parameter fine-tuning.

RNN-LSTM Inference Model Creation: This part involves the creation of the inference RNN-LSTM network model. Using the framework, the trained RNN-LSTM network model and the link weights are properly bundled and achieved in a file, with minimal metadata. The RNN-LSTM inference model can now be applied to achieve the prediction of new future traffic demands.

Step 2 (Energy-Efficient Routing Modelling): Primarily, energy-efficient routing modelling is concerned with the computation of traffic routing configurations, aimed at minimising energy utilization in the present time-slot, while requiring the least number of routing configurations to stay optimal. Recall that network re-optimization occurs at the end of the time slot. At a given time-slot, the optimization model considers the prediction horizon (range) of the time-slots. Therefore, to address the goal of minimising energy utilization with the least amount of routing configurations, the prediction algorithm is applied to generate energy rate predictions and energy consumption values. To achieve the above requirement, this work employs an energy-efficient route re-optimization algorithm.

Energy-Efficient Route Re-Optimization Algorithm: Energy-efficient route re-optimization algorithmic model is one employed on the data rates to predict energy rate values and reduce future network reconfigurations, according to the predicted flow bandwidth. To construct the energy-efficient routing optimization model, we use the previous data rate predictions. Moreover, the refine algorithm is routinely employed to explore the search space of prospective energy-efficient routing parameters. These parameters are required to build a sequence of energy-efficient routing models and compare them based on the appropriate route re-optimization metrics. Afterward, the predicted parameters are employed by the optimization algorithm to achieve the desired ends.

But, since the complexity of the route re-optimization model grows owing to the increasing number of pre-recalculated paths, number of traffic flows and the length of prediction horizon or time-steps, it is NP-hard problem. Currently, many approaches are used to solve such NP-hard problems, including greedy algorithms and GA. This work considers the use of GA to solve the NP-hard problem [106].

ii) Result and Analysis: This is the final phase mainly concerned with the use of the inference RNN-LSTM model to compute energy rate predictions and the network routing re-configuration, to ultimately generate optimised energy-efficient routes. The methodology description above was dedicated to the supervised ML module. Principally, the supervised ML module is dependent on the availability of historical data. Recall that in the absences of historical data, execution control is transferred by the ML engine to the unsupervised DRL algorithmic module.

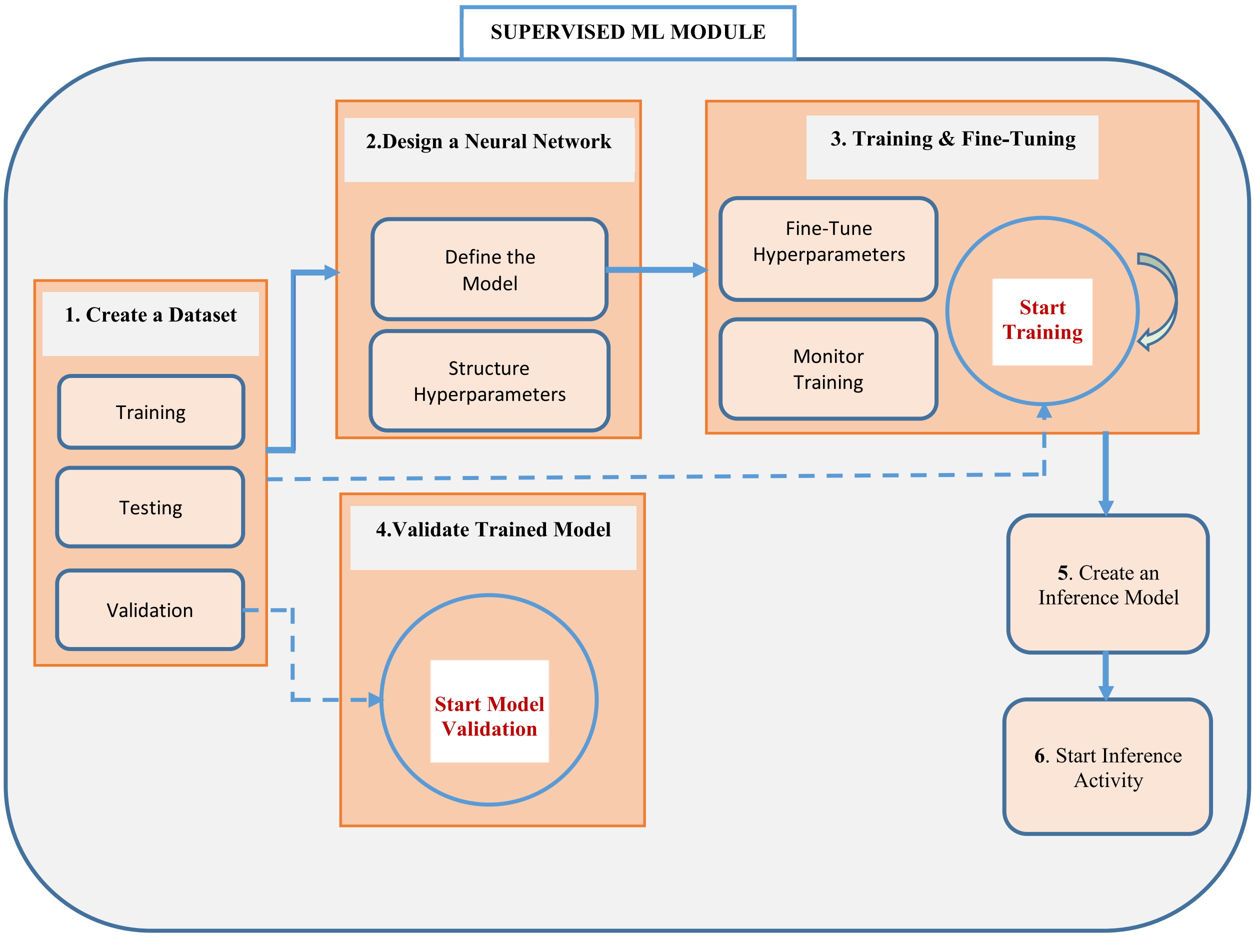

FIGURE 8. **Sequential training, testing and validation process of the supervised ML module.**

In the context of RL, the Markov Decision Process (MDP) is a useful mathematical framework for tackling related problems. The MDP is an abstract framing of the problem of learning via interaction to achieve a certain control and optimization goal.

b: UNSUPERVISED DRL MODULE

This part of the methodology considers the unsupervised DRL module, which is an algorithmic framework whose objective is to achieve the TE goal of energy-efficient routing optimization with QoS-based performance guarantees. In the perspective of RL, choice of a suitable mathematical framework to address the above objective is critical. In this work we consider the use of Markov Decision Framework (MDP). MDP is a generalised architectural framework used to model decision-making problems in scenarios where the outcome is partly random and influenced by applying a given decision. Precisely, MDP represents and abstract representation of learning problems through interaction to achieve a target control and optimization goal. This work addresses the objective by representing the TE problem as a multi-agent MDP (MA-MDP) [155]–[157].

Moreover, the proposed DRL module provides a smart network traffic control architecture composed of an offline DNN construction (configuration) phase and a self-taught on-line updating (training) phase. The on-line update phase is based on deep Q-learning. By implementation, the online DRL algorithmic framework can be deployed in any existing network routing protocol to enhance or develop a novel routing solution. Clearly, it presents a baseline algorithmic protocol independent solution.

Additionally, the module is based on a set of agents (router nodes) that communicate in the environment with the goal of learning the reward maximization behavior. The module examines E2E energy-saving in network routing coupled with performance guarantees based on future reconfiguration re-routing to support traffic demands. The module assumes a real-life network environment with known state transition probability and reward distribution. This is the exact context in which the agent-based DRL module is suggested. Principally, the framework is developed on the basis of the generalized policy iteration strategy, which leverages the novel and increasingly popular policy gradient enabled learning, coupled with function approximation, in a multi-agent-based

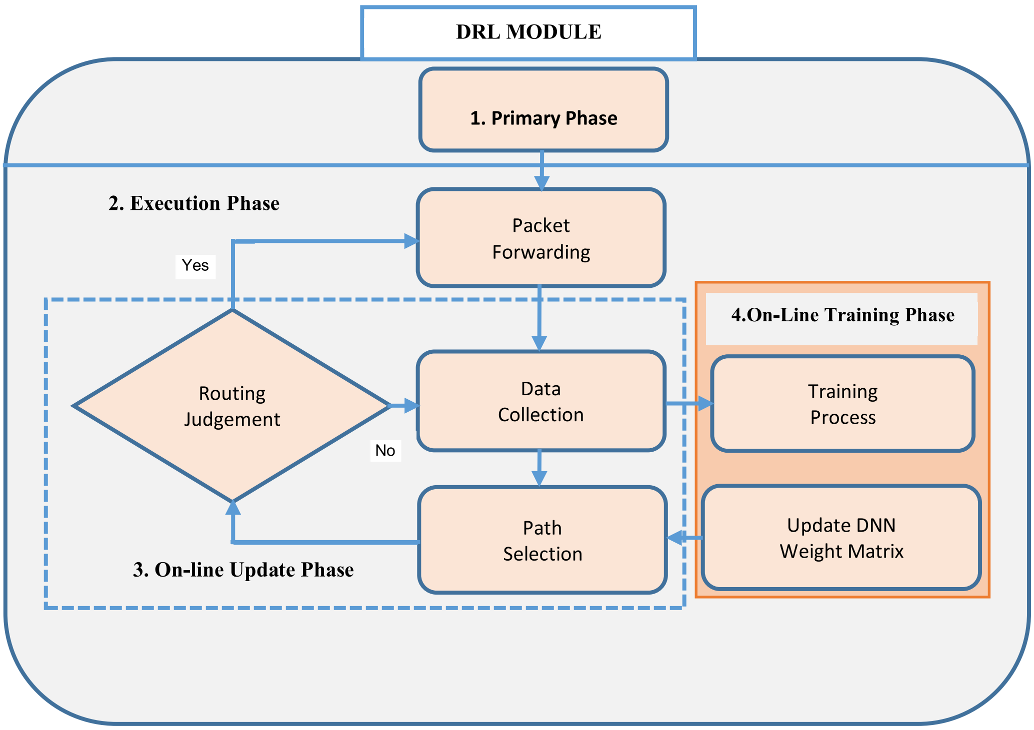

FIGURE 9. The execution process of the unsupervised DRL module.

scenario [70]. To achieve the above, the algorithmic module learns the next-hop to which each router's packet is forwarded. This task is continued all through the target destinations, while taking into account the optimal E2E TE performance.

Further, we consider joint energy-efficiency and performance optimization with QoS metrics that include delay and throughput. In the current setting, the ML engine and the network environment construct a MDP environment to ensure continuous interaction, to generate control strategies. Moreover, by extending the MDP, the DRL module is formulated based on the defined set of communicating agent-based routers whose behaviour is characterized by various parameters that include state, observation, action, state transition probability function and rewards.

As stated in Section II, we aim to alleviate the energy-efficient routing problem by integrating the pinning control theory with DRL module to manage the hybrid network [119]. This requires the selection of a subset of the routing nodes which become the controllable agent nodes. Then, we permit the DRL module to manipulate the link weights of the controllable agent nodes, ultimately to ensure improved global network performance. Moreover, we employ DNN to process the input data in the DRL module.

Provided in Fig. 9 is an illustration of the sequential training, testing and validation process of the DRL module. Additionally, provided in **Table 16** is a summary of the required state spaces (elements) of the DRL processes performed by each agent in the environment.

As an extension, the DRL module considers an agent-based process consisting of four interleaving phases which include: primary (policy estimation) phase; (policy) execution phase, online (policy) update phase and training phase. To solve the problem, a modular DRL Q-learning framework is proposed.

As previously stated, the running of the DRL module is triggered when a change occurs in the network environment, due to the arrival of a new flow or occurrence of the network state update. Next, the ML engine performs the interleaving process, among the various processes. Basically, the ML engine manages the interface between the agent controller and the environment, using a series of decision making epochs. Provided below is a description of the four phases considered in the running of the DRL module.

1. Primary Phase: In a precondition to performing the execution phase of the supervised DRL module, several important tasks must be undertaken by the respective routers, including definition of the routing strategy.

This work employs the Deep Deterministic Policy Gradient (DDPG) automatic routing algorithmic approach to perform intelligent control and hence address the energy-efficient routing optimization TE problem [158]. The DDPG approach is made up of two components which include the deterministic policy network (actor) and the Q-network (critic). Whereas the actor component tries to improve the policy, the critic counterpart performs the evaluation of the quality of the existing policy by using parameters. Precisely, the DDPG agent performs the implementation of an iterative policy mechanism which interleaves between policy update (actor) and policy estimation (critic).

2. Execution Phase: The execution phase is composed of two different periods and these include the cold booting and smart execution.

(a) Cold Booting Period: Cold booting period represents the off-line starting period that precedes the training phase. The goal of cold booting is to derive the correlation amongst respective state-action pairs in the system and the corresponding value functions. This action is performed to enable the system populate the weights and select the minimum policy, taken as the first energy-efficient routing pool. Later, the training phase is performed to construct the DRL-NN by learning sufficient states-action signal pairs and the value functions in the updating phase. The action signal represents the energy-efficient routing judgement of the updating phase. **Policy Mapping:** In the DRL module, the policy unit is employed to define a mapping that chooses an action based on the state of the network environment. Like previously stated, a policy represents a mapping from each state-action pair, specifying the action the agent will select when the environment assumes a given state. In other words, it represents an approximation function with tunable parameters, for instance a DRL-NN network. Recall that the ultimate goal is to determine the optimal policy, which maximizes the reward for each state, based on discount rates.

(b) Smart Execution Period: When the agent controller (the supervisor agent) generates sufficient training data, and on completion of the training phase, the system performs a transition to the smart execution period. During this period, the real-time updating phase is performed on a routine basis. Also, the valid E2E energy-efficient path pool is intelligently selected and applied based on the outcome of the energy-efficient routing judgement within the updating phase.

3. On-line Update Phase: The online updating phase performs the collection of traffic patterns needed for training. It also performs the routing judgement task to smartly select the valid path pool. This pool is used to determine the most appropriate routing path to overcome congestion and balance the load. The update phase is divided into two: data collection; and path selection and routing judgement.

(a) Data Collection: This is concerned with the collection of the routing information and traffic flow patterns or statistics, with subsequent updates at the agent controller. These tasks are performed based on the defined update interval or period.

As soon as the destination router detects data packet arrival, it records QoS parameters such as the transmission delay of each packet. For the duration of the update phase, the agent controller captures the routing strategy combination of the individual routers, as previously stated. Beside, individual routers compute parameters such as packet loss and average packet delay, within the duration of the previous and current update phases, and these are delivered to the agent controller. Then, a threshold is computed during the updating interval to determine the event of congestion and hence balance the load. The threshold value is computed using the maximum and minimum values of the total intervals. Additionally, the traffic patterns that include packet extraction rate and the size of waiting packets in the queue at each routers buffer are recorded. Together, the state of network congestion and traffic patterns are pooled to produce labeled training data sets. On performing several update operation phases, a sufficiently large volume of training data set is attained to train the DRL-NN network architecture. This marks the initiation of the training phase.

(b) Path Routing and Judgement: In order to make a decision on the occurrence of routing, we consider the agent controller that implements a specific routing strategy, with matching DRL-NN applied to determine if the current network traffic patterns can lead to congestion event or otherwise. In case the outcome reveals the occurrence of congestion, such a path is marked as invalid, in which case the routers can select the next combination and repeat the judgement, until a valid combination of path is selected.

4. On-line Training Phase: The online training phase is concerned with construction and enhancement of the deep neural network. Moreover, the online phase handles the adaptive generation of the optimal policy action and updates of the policy value estimations. Specifically, the training phase performs the training and learning of the state of network congestion of a very combination strategy. When the training data is generated at the on-line update phase, the DRL LSTM model is constructed, based on the total path combination strategy.

As previously stated, assuming the network route is already created, the training process commences with the aim of improving the DRL LSTM network architecture. Precisely, the weight matrices of the trained DNN which are used in the on-line update phase to make a decision. Based on the on-line training algorithm, the DNN is trained in a periodic manner using defined time interval. One observation is, by setting a large number of updating period, we can generate sufficient labelled training data. Thus, over time the neural network can be enhanced to route with a higher level of accuracy.

E. LSTM-RNN NETWORK ARCHITECTURE

The previous section considered the proposed methodology, based on supervised DRL module and unsupervised DRL module. This section delves deeper into deep learning LSTM-RNN network architecture.

As previously stated, the supervised ML module is designed to employ the innovative deep learning LSTM-RNN network architecture in such hybrid SDN/OSPF network. Recall that a major problem in existing hybrid SDN/OSPF networks concerns the optimization of network traffic prediction and energy-efficient routing with QoS-guaranteed performance. To deal with the problem, a number of challenges have been identified and these need to be tackled head-on This work has previously discussed various challenges which we restate in this part: first, the use of traditional

TABLE 16. Elements of the DRL agent-based processes.

Parameter	Description
State Space	This work considers a state space made up of three measures, that include E2E energy-efficiency values, throughput and delay. The state space is denoted by a matrix of throughput (requiring): the length of time steps of DNN, number of flow types and total of observed ports of the controlled router nodes in the network. Such state space is defined from the agent-based periodically collected set of network traffic status information from the network environment.
Action Space	Refers to the traffic routing policy obtained by the agent to improve network utilization. We consider examples of multipath split ratio and the weight of individual links. The action space (matrix) is denoted by a weight matrix which specifies the link weight of the controlled nodes: of throughput (requiring): the total flow types, and the total of controlled network links.
Reward Function	This refers to the objective of the routing algorithm and it is defined using E2E-TE metrics to be optimized. This work considers the optimization of energy-savings and performance metrics that include delays and throughput. Moreover, we set the average flow completion time of all the flows as the reward.

heuristic-based routing algorithms in hybrid SDN/OSPF lead to slow network convergence and slow response which challenge energy-efficient routing optimization with QoS guarantee; second, the scarcity of adequate labelled data required to train and learn the built NN models in SDN-based ML and DL system; third, the difficulty in perform precise hyper-parameter tuning for DL networks, due to the dynamicity of the network environment, mainly characterized by time-varying network topology and traffic load. Therefore, to optimize the trade-off between energy-efficient routing and network performance with QoS guarantees in such hybrid networks, we propose and focus on a supervised ML architectural framework that is based on LSTM-RNN network architecture.

1) LSTM-RNN NETWORK ARCHITECTURE BY STRUCTURE

Like traditional RNN, the architecture of the DL LSTM-RNN network architecture is made up of one input layer, a single hidden layer (which is divided into many sub-layers) and a single output layer [75], an illustration of which is given in Fig. 10.

During feature extraction phase, the input layer is employed for data input in form of times series, which feeds into the deep network architecture. Moreover, the LSTM layers perform the learning of long-term dependences amidst the time-steps of the data series. As shown in the figure, the network basically starts with a sequence of input layer, then it progresses to LSTM layer, to eventually end at the fully connected layer. At this level, an important requirement which must be emphasised involves the extraction of periodicities and short term disparity during specific time-steps. Addressing such a requirement is key to building a deeper network estimation model [159]. To properly extract such important dependencies and short term disparity features, two novel LSTM memory units are employed.

After extraction, the features are fed to feature stage amalgamation to ensure short-term traffic flow prediction. As revealed in Fig. 10, the desired variable represents the captured network traffic in the previous time period, and this is represented as X_{t+2}, X_{t+1}, X_t, X_{t-1}, X_{t-2}. Observe that many LSTM-RNN cells are stacked in the form of many-to-many model. This basically means that merely one single cell in the final time-step and more so in the uppermost value output, is destined for the regression phase.

2) LSTM MEMORY CELL

Specifically, the core concept of LSTM network architecture is the memory cell which is within the hidden layers [159], this being because it is designed with the aim to overcome gradient vanish and explosion problem. Recall that this problem is a major challenge in traditional RNN [75], [160] Basically, the LSTM memory cell is made up of four (4) key parts which include input gate, a self-recurrent connectivity neuron, forget gate and the output gate. Observe that a major implementation consideration in LSTM networks is the need for adequate labelled data, both input and corresponding output to ensure better learning outcome. Thus, to fulfil the need to achieve a better learning outcome, more training data should be provided. If there is limited training data, the LSTM network can obtain a high training accuracy, however it can perform poorly when test runs are done on unseen data. Precisely, this condition is referred to as overfitting.

F. GENERIC DRL ARCHITECTURAL FRAMEWORK

The previous section considered the deep learning LSTM-RNN network architecture. This section is devoted to a detailed description of the proposed generic DRL architectural framework. We give an array of potential deep learning algorithms and how these are supported in the generic framework. Precisely, we spell out potential application scenarios, in the generic framework.

1) OVERVIEW

To provide a suitable solution, we consider a generic DRL architectural framework, precisely designed with the goal to teach the constructed DNN on how to learn with limited data.

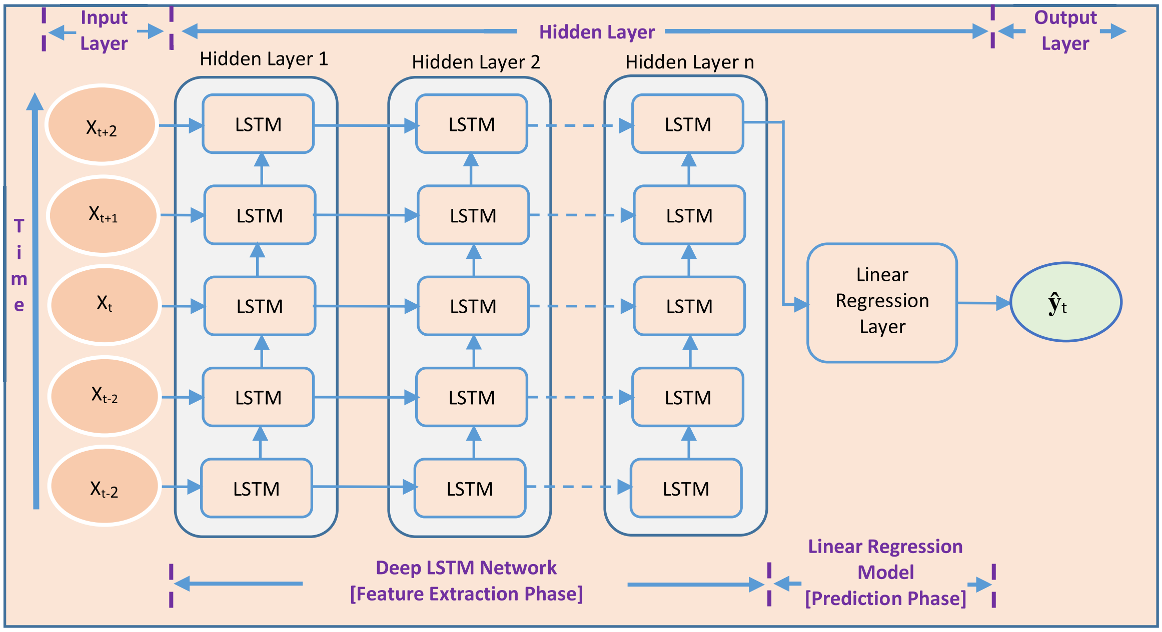

FIGURE 10. **LSTM-RNN architecture with feature extraction to the left and regression prediction to the right.**

Also, we consider training and learning the NN on how to pool its knowledge to improve efficiency and effectiveness, in the learning of new events. Such a strategic effort can ultimately minimize the amount of training data needed. Basically, the new generic framework shares similar fundamental concepts with RL frameworks. But, before delving into the details of the new framework, it is rational to restate the current network condition, specifically the current problem in such communication networks.

Recently, ML techniques such as RL have increasingly gained popularity in light of network control and operations management. Although, certain networking studies have employed RL techniques to address various networking problems a number of major challenges need to be resolved: first is the inability of RL-agent based techniques to support the generalization over unseen network states, to deliver working solutions [109], [115]; second, existing traditional ML heuristic algorithmic approaches can hardly achieve convergence due to the time consuming off-line multi-step iterative synthesis (optimization process). These issues demand for research efforts to engineer novel solutions, to respond to the diverse requirements in modern large-sized dynamic networks.

To address the stated problems, this work considered a new generic DRL architectural framework. The considered generic framework is made up of an SDN-based agent-environment communication procedure. Given such a configuration and based on the terminology in use, we term the learner and decision taker as the agent. In the proposed framework, the agent and environment interface based on a succession of decision-making epochs (periods). Like previously stated, the generic framework is composed of an off-line DNN buildup phase and a self-taught on-line Deep Q-learning phase. On the one hand, the off-line DNN buildup phase of the framework performs the role of generating the correlations between the respective state-action pairs of the network system and its value function. On the other hand, the deep Q-learning phase is responsible for generation of the optimal action and update of the value estimates.

As provided in Fig. 11, we consider a generic representation of a self-taught modular DRL architectural framework, which is a non-linear architecture designed to respond to current complex control problems in the emerging large-sized dynamic SDN-based networks. Such large-sized networks complexities pose implementation challenges, such as computational complexity and determination of the gains and parameter tuning.

2) DESIGN OBJECTIVE

The design objective of the generic framework is to compute the of optimum policy behavior, that performs the mapping of the state space to the multiple actions, to ultimately maximize the target reward value.

3) THE GENERIC FRAMEWORK AND ALGORITHMIC SUPPORT

The generic framework is composed of a universal agent-based interaction environment, which is an expansive buildup system that pools together and supports the implementation of a diversity of various algorithms [161]–[163]. The universal agent-based interaction environment is devised to support the use of various DL algorithmic techniques such as deep Q-learning and double Q-learning. Precisely, based on these techniques the universal agent-based environment can support the application of different agents such as Q-learning, SARSA, deep Q-Network, deep deterministic

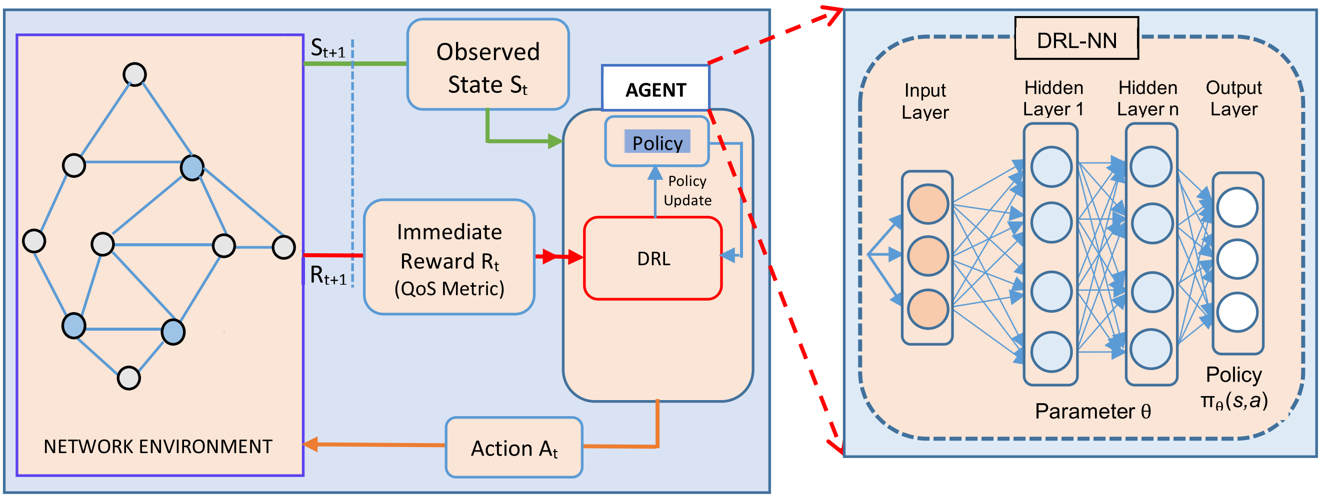

FIGURE 11. Generic DRL architectural framework.

policy gradient (DDPG), twin-delayed deep deterministic policy gradient, actor-critic and proximal policy optimization. To achieve the objective of the generic framework, we consider an SDN-enabled agent unit, which is employed to perform and complete the desired task in an uncertain environment.

4) THE SDN-ENABLED AGENT UNIT

As illustrated in Fig. 11, the generic framework is composed of SDN-enabled agent-based learning unit. The agent is a major component that is structured into two subunits, namely a policy and a DRL algorithm. The agent and the environment interface based on a series of decision-making epochs (periods). The ultimate aim of the agent is to determine the optimal policy that maximizes the reward for each state, based on discount rates. Moreover, SDN-enabled network is embraced to provide the global network status. Basically, global network visibility status is critical in the realization of intelligent decision making requirement of the unit. Besides, it allows the generation of the network strategy and the respective rules from the control plane, this being based on the target strategy.

5) EXECUTION

To implement the generic framework and achieve the desired goal, this work considers the that the agent unit and the environment interface based on a series of decision-making epochs (periods). Given a specific decision-making epoch, the agent-based unit receives the state (observation) signal S. This signal emanates from and is a representation of a certain state of the environment. Partially, based on this signal, the agent selects an action A. Then, it receives the state (observation) signal and a numerical reward signal coming from the network environment. Moreover, it forwards the actions signal to the network environment Given this, the agent discovers itself in a different state of the environment. Then, the reward signal measures how an action signal has been successful against the target activity goal.

6) POLICY SUBUNIT

The policy subunit of the agent defines a mapping that chooses an action based on the state from the network environment. Normally, a policy is denoted by π, for the agent. A policy represents a mapping from each state-action pair which specifies the action A= π(S) which the agent will select when the environment gets to a given state S. Overall, a policy represents an approximation function with tunable parameters, for instance a DNN network. Recall that the ultimate aim of the SDN-enabled agent is to determine the optimal policy, which maximizes the reward for each state, based on discount rates.

7) DRL ALGORITHM SUBUNIT

The DRL algorithmic subunit of the agent is charged with the determination of the optimal policy to maximize the cumulative reward, obtained in the course of the target activity goal [139]. As shown in Fig. 11, such a requirement is achieved through regular updates on the policy metrics using the actions A_t, state S_t and the rewards R_t. By using this procedure, the generic architectural framework can now address the concern of exceedingly enormous state space, including infinite continuous state space, by principally using of both off-line trained and on-line updated DNN. Moreover, it is rational to keep such an action space at a reasonable size, given the action space enumeration constraint to ensure action selection.

G. IMPLEMENTATION OF THE HYBRID ML AND DRL ARCHITECTURAL FRAMEWORK

In section (E), we discussed the proposed generic DRL architectural framework. Provided in this section is a description of the implementation process of the conjoint supervised ML

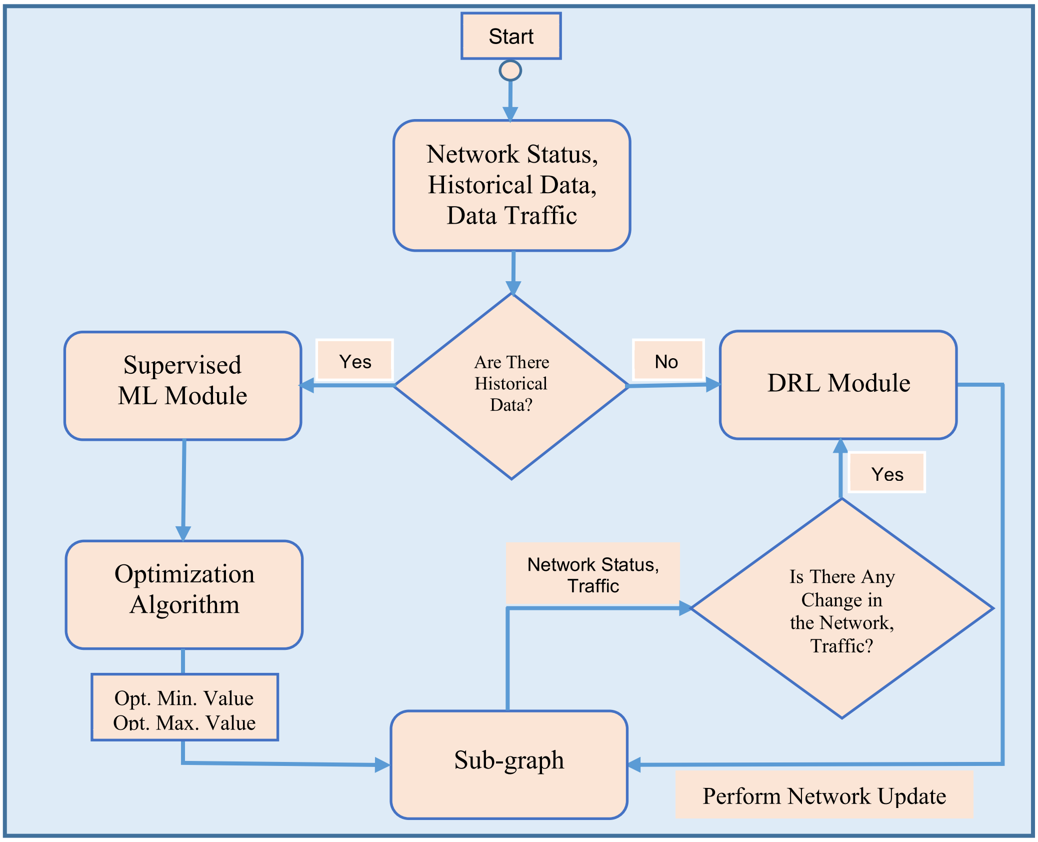

FIGURE 12. Implementation of the hybrid ML and DRL architectural framework.

and DRL architectural framework in the generic DRL framework. Provided in Fig. 12 is an illustration of the execution algorithmic procedure of the proposed conjoint supervised ML and DRL architectural framework, in hybrid SDN/OSPF networks. Generally, the hybrid ML and DRL architectural framework is comprised of two algorithmic modules, precisely the supervised ML and non-supervised RL modules. The supervised algorithmic module is composed of the PCA and the refine algorithmic techniques. Besides, the unsupervised DRL algorithmic module is composed of Q-routing algorithm technique. Among these, the refine and Q-routing algorithms belong to a class of HAs. Prior to execution, one consideration which determines the choice of the initial algorithm to begin with is the availability of data. With the availability of historical data, the supervised ML algorithmic module becomes the startup module.

As shown in the figure, the process begins with the supervised ML module which employs the PCA techniques to perform feature representation and feature dimension reduction, and model training and testing. Then, the refined GA is applied to predict the optimal routing parameters. Afterward, the predicted parameters are employed by the optimization algorithm to achieve the desired outcomes. Assuming that a change occurs in the network environment, mainly brought about by the arrival of a new flow or update in the network state, rather than performing prediction and execution of the optimization algorithm again, the unsupervised DRL module behaves relatively and responds easily to such variability in the environment. In a condition where no historical data exists, the DRL module can employ Q-routing heuristics to learn energy-efficient paths for data traffic flows.

VIII. CONCLUSION

The intersection between AI-based ML and DL, and SDN is increasingly gaining popularity and is envisioned to play a pivotal role in the advancement of current and next generation communication networks and services. This paper has on the one hand provided an updated review of selected load balancing and energy-efficient routing solution in hybrid SDN/OSPF networks. On the other hand, the paper gives a review of the most recent ML and DL algorithmic frameworks, mainly employed in traffic prediction and energy-efficient routing in SDN-enabled networks. First, the paper gives a brief discussion of SDN architecture. Second, the paper considers background to hybrid SDN/OSPF networking. Third, we discuss key selected works in hybrid SDN/OSPF domain. Fourth, a discussion of selected ML and DL studies provided. Fifth, the paper discusses the benefits and the challenges that demand for innovative working solutions. Sixth, based on the outcomes of recent studies, recommendations are made to guide future research for obtain better outcomes. Lastly, the paper proposes an algorithmic framework that leverages conjoint supervised ML and DRL techniques to ensure traffic prediction, and cost-effective, rate adaptive energy-efficient routing and performance guarantees in such hybrid networks. We believe that this work will play an important role in guiding the communications research community and other practitioners with interest to apply AI-based ML and DL in addressing the complexities that exist in current and next generation SDN-enabled networks.

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