Survey of Routing Techniques-Based Optimization of Energy Consumption in SD-DCN

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Abstract—**The increasing power consumption of Data Center Networks (DCN) is becoming a major concern for network operators. The object of this paper is to provide a survey of state-of-the-art methods for reducing energy consumption via (1) enhanced scheduling and (2) enhanced aggregation of traffic flows using Software-Defined Networks (SDN), focusing on the advantages and disadvantages of these approaches. We tackle a gap in the literature for a review of SDN-based energy saving techniques and discuss the limitations of multi-controller solutions in terms of constraints on their performance. The main finding of this survey paper is that the two classes of SDN- based methods, scheduling and flow aggregation, significantly reduce energy consumption in DCNs. We also suggest that Machine Learning has the potential to further improve these classes of solutions and argue that hybrid ML-based solutions are the next frontier for the field. The perspective gained as a consequence of this analysis is that advanced ML-based solutions and multi-controller-based solutions may address the limitations of the state-of-the-art, and should be further explored for energy optimization in DCNs.**

Index Terms—**Data Center, Software-Defined Networking, Integer Programming, Power Consumption, Energy, Routing.**

I. Introduction

The power optimization increasingly attracts many researchers in different sectors of wire and wireless networks [1]–[4]. Specifically, large-scale alternatives to fossil fuels that are secure, affordable, and low-carbon are lacking globally. The connection between access to energy and greenhouse gas emissions is the aspect of energy that receives the most attention. On one hand, Europe's energy grid is facing an unparalleled crisis [5]. Since early 2021, wholesale costs of electricity and gas have increased by as much as 15 times, which has had devastating consequences on both individuals and companies. On the other hand, the huge demand for information services nowadays is causing a dramatic increase in the usage of Data Center Networks (DCN) around the globe. As a consequence, 1 % to 1.5 % of worldwide power consumption is attributed to data center energy usage [6]. According to [7], the increase in power consumption in DCN has been 56% between 2005 and 2010 and it is expected to continue to increase in the future. Current estimates suggest that by 2020, the energy consumption of DCN in the US exceeded 139 billion kWh, and that interconnection devices (switches and links) consumed from 10 % to 20 % of the total energy [8]. The need for building effective network solutions in terms of energy usage and latency has expanded tremendously due to Industry 4.0's and the IoT's rapid development. Alternative techniques are required to address the power consumption issue in DCN. Software Defined Networking (SDN) is a new networking paradigm which can address power consumption. Compared to the legacy network architecture, SDNs have been effectively implemented in a variety of domains to satisfy the needs of the smart industry [9]. It is characterized by physically decoupling the control and data planes. The logically centralized SDN controller orchestrates the policy of the forwarding elements residing on its domain. The advantages of SDN has led to the incorporation of its architecture into a wide range of solutions. For instance, SDNs demonstrated promising results in optimizing the networks power consumption [10]. The term Software-Defined Data Center Networks (SD-DCN) emerged due to the employment of SDN to address various DCN issues such as the energy consumption. There are a number of studies that employed SDN in data centers to enhance the network management in general and to lower the power consumption.

This paper surveys the energy efficiency potential of SDN in enhancing power utilization through the optimization of traffic-aware features of DCNs. SDN has emerged as a critical paradigm for achieving the Network Resource Optimization (NRO) and for dynamically optimizing the network based on load and state. This is the most common carrier application as it optimizes the network using the near-real-time state of traffic, topology, and equipment. NRO uses a variety of southbound protocols (for example, NETCONF, BGP-LS, or OpenFlow) depending on the underlying network [11]. According to the literature, researchers address the problem by considering both hardware and software enhancement. In brief, the energy-saving technologies of hardware focus on frequency scaling techniques (i.e., changing clock frequencies). The motivating idea is that the power is consumed is a function of the working clock rate [12]. In the same context, other researchers optimize power consumption performance by consolidating multiple Virtual Machines (VM) in one physical machine [13]. Quality of Serivce (QoS) is upheld in these approaches by imposing multiple constraints. Routing-aware approaches have appeared in recent years. DCN topologies (i.e., fat-tree, Bcube, etc) come with rich connections and can achieve high network performance by balancing the workload of the DCN, however,

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such structure of the DCN topology wastes energy since traffic volume is not proportional to energy consumption of DCN equipment, especially in the traffic valley time [14].

This paper reviews software-based energy-efficient solutions in the form of subcategories of the traffic-aware approaches. The structure of this paper is organized as follows. We start by classifying data center routing optimization methods and by showing the advantages and disadvantages of each technique in Section II. Then, we discuss the open challenges for the existing implementation approaches along with the potential future directions in Section III. Finally, we provide our conclusions in Section IV.

II. Routing Optimization Techniques

Power consumption of SDN-based DCN routing mechanisms depend on the mode of operation of the set of switches that forward the flows between sources and destinations. Power consumption of DCN switches can be measured in two ways: *dynamic*, which measures the power consumption of active links, and *static*, which measures the sum of power consumed by components such as chassis, fans, and switching fabric. We adopt the following notation conventions. An directed weighted graph, $G = (\mathbb{S}, \mathbb{E})$, models the network topology. The vertex-set is denoted by $\mathbb{S} = \{s_1, s_2, \ldots, s_n\}$, and the edge-set is denoted by $\mathbb{E} \subseteq \{e_{ij} \mid s_i, s_j \in \mathbb{S}\}$. The i-th switch is denoted as s_i and represents an OpenFlow switch. The primary function of each switch is to facilitate the routing of information through the path determined by the network controller. In the graph, G, every edge represents a link, and the link connecting the i-th and j-th switches is identified by e_{ij}. Network links can exist in either an active (ON) or inactive (OFF) state. We use binary variables, denoted by L_{ij}, to indicate the current state of network links. The variable L_{ij} is 1 if the link connecting switches i and j is active. This means that it can transmit packets between two ports. Conversely, L_{ij} is 0 if the link is inactive. In practice, each link consists of two ports, a sending port and a receiving port. Therefore, when designing power-efficient routing the working ports of each link should be considered. Similarly, the variable, ℓ_i, is set to 1 if the switch is active and 0 if the switch is inactive. The Network Power Consumption (NPC) is given in (1).

$$\text{NPC} = S_p \sum_{s_i \in \mathbb{S}} \ell_i + D_p \sum_{e_{ij} \in \mathbb{E}} L_{ij}. \tag{1}$$

Eqn. (1) relates the NPC to ℓ_i and L_{ij}, which denote the state of a corresponding switch, s_i, and link, e_{ij}, i.e., whether they are turned on or off. The variables D_p and S_p denote whether the power consumption is dynamic or static, respectively.

The authors analyzed the traffic of a wide range of DCN network datasets belonging to different layers of DCN topologies in [15]. The results reported in this paper showed that the link utilization was low and varied from one layer to another. The low-utilization links motivated researchers to propose new approaches that were more energy-aware than commonly used routing algorithms (e.g., Equal Cost Multiple Path (ECMP)). To address this problem, two types of methods have been proposed: (1) flow aggregation techniques and (2) flow scheduling techniques.

A. Flow Aggregation Techniques

Flow aggregation techniques consolidate data flows into a smaller set of links and switches that are sufficient to support existing data traffic demands, subject to a tolerance to a certain level of delay, packets loss, etc. To achieve minimum power consumption for a specific traffic matrix, switches and ports that are being used unnecessarily are put into sleep or shutdown mode. Fig. 1a shows how three flows share one link fairly based on the Transmission Control Protocol (TCP) sharing scheme. The disadvantage of these techniques is that using only a subset of the switches and links, a sub-topology, may result in performance degradation, which is typically characterized by a QoS measure. This QoS measure may indicate the significance of increases in delay time (i.e., due to computational complexity of the output solutions), or the extent to which links with higher utilization become overloaded and more susceptible to unplanned failures [16]. Balancing between the level of energy consumption and routing techniques that meet a desired QoS is of great importance. Next, we introduce and discuss the concept of flow aggregation.

1) Elastic-Trees: Need for Correlation-aware Power Optimization: The first analysis on Elastic-Trees (ET) was published in 2010 [17] by researchers from Deutsche Telekom and Stanford University. They considered three optimization techniques: Linear Optimizers (LO), Greedy Optimizers (GO), and ET. All of these optimizers work to consolidate traffic into a small subset of links that can handle the traffic volume. The results showed that LO are the worst due to their high computational complexity and time cost when the number of switches is high, while ET outperformed GO and improved link switch utilization. The authors evaluated ET using both simulations and experiments on a real network. They found that compared to traditional network architectures it could save significant amounts of energy. However, the study did not consider the correlation between flows. To address the high correlation between flows, the CARPO (CoRrelation-aware Power Optimization) algorithm in [18] aiming to reduce energy consumption in a DCN, dynamically consolidated traffic flows on a small set of links and switches, and switched off idle network components. CARPO uses correlation analysis among flows to consolidate traffic flows with low correlation while keeping the QoS at an acceptable level. A heuristic algorithm is used to find a consolidation and rate configuration solution with acceptable runtime overheads. CARPO introduced parameters to represent flow correlation, and the results showed that this extension of the ET, led to a power saving of 46 %.

The study in [12] suggested a platform composed of both software and hardware components, because there was no experimental environment available to test the optimization model. The software part was composed of monitoring (to check the state of the network), an optimizer (to calculate the subset of the topology), power controller (to change the state of the devices on/off), and routing algorithm (to calculate the paths). The hardware parts were composed of a traffic generator and power measuring device implemented using the NetFPGA platform. Experiments investigated the effect

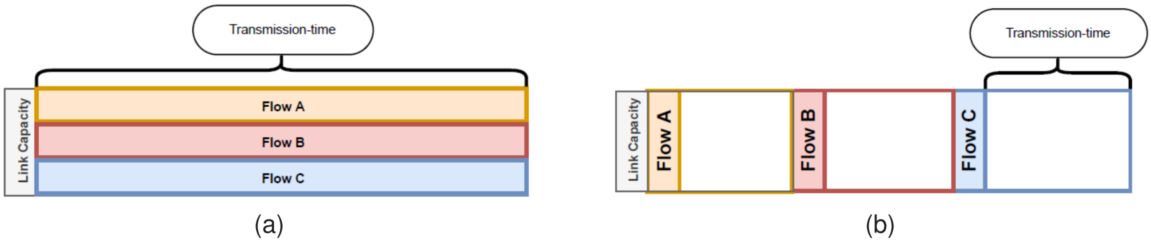

Figure 1. Flow scheduling & flow aggregation routing illustration. (a) Flow aggregation. (b) Flow scheduling.

of changing the frequency of the clock rate and the traffic consolidation on the power consumption in the DCN according to traffic demand. Unfortunately, the authors did not provide sufficient details about the algorithms or the API interfaces that gave access to the components.

The authors reported that the traffic patterns of GEANT networks are generally regular and predictable in [19]. To save power, they divided the traffic into intervals, and implemented link sleeping, which temporarily suspends certain links when the minimum or maximum link utility thresholds were met. They also rerouted the flows among the nodes of the GEANT network topology to maximize flow through the active links. Additionally, the study considered the network's performance under high-traffic conditions and balanced the traffic appropriately. The study described in the paper by Conterato et al. in [20] investigated the effect of using different values of over-subscription factors on reducing power consumption in a DCN, which was using traffic aggregation strategies. Three algorithms, First-Fit, Best-Fit, and Worst-Fit, were evaluated using Python and the Network Simulation Setup (FNSS). Different network workloads (20 %, 50 %, and 80 %) and oversubscription factors ($1:1$, $1:5$, and $1:20$) were tested. Devices that were not enrolled in the current routing state of the network were disconnected. The authors reported that up to a 70.02 % power saving could be achieved when the over-subscription factor was $1:20$ and the topology size was $k = 12$. These results conform with intuition because of the increase in the bandwidth and the number of links and switches in the topology. Motivated by the need for an adaptive routing framework for SD-DCN that can optimize power consumption while maintaining good network performance, the authors of [14] proposed an adaptive routing algorithm that considers factors such as link utilization and switch power consumption to determine the most energy-efficient path for network traffic in real-time. The algorithm used an Integer Linear Programming (ILP) model and a heuristic algorithm. The authors argue that the ILP model is costly and the time for finding a solution increases dramatically when 100 flows are injected simultaneously into the DCN. Conversely, the algorithm is integrated into an SDN controller and uses the OpenFlow protocol to communicate with switches. The proposed algorithms outperform existing routing algorithms such as ECMP in terms of energy consumption and network performance, as measured by the number of dropped packets. The research group built on this work and contributed new findings for the ILP model in [21]. Evaluations were conducted using LINGO [22], which is one of the computationally expensive commercial solvers. The authors of [14] re-implemented the model using solvers such as Gurobi, CP-SAT, and so on. Experiments were implemented in the authors' proposed tool neO-DCN. This comparison revealed that Gurobi outperformed the other solvers by one or two orders of magnitude for different traffic patterns.

OpenFlow switches are increasingly being used in data centers due to their potential to reduce energy consumption. However, the existing OpenFlow protocol does not include any mechanisms to optimize energy consumption. In [23], a power-aware extension to the OpenFlow protocol that does not compromise network performance was proposed. The extension defined new control messages in the OpenFlow standard such as OFPT-ORT-MOD and designed an OpenFlow Switch Controller (OSC) that can turn on and off switches and disable-enable ports of NetFPGA-based OpenFlow switches [12]. The authors conducted experiments to evaluate the energy savings achieved by the proposed extension, using a prototype implementation of the proposed extension on an OpenFlow switch. The experiments were designed to evaluate the energy savings achieved by the proposed extension. However, the authors did not provide sufficient details about the methods and the experiments conducted. Further research is needed to evaluate the effectiveness of these extensions. Table I summarizes the flow aggregation methods according to the adopted evaluation criteria and the main objectives.

2) Formulation: To optimize power consumption in DCNs, we present a general formulation of the objective function and constraints which describe an ILP model. The purpose of this ILP is to determine the optimum flow aggregation technique to reduce energy consumption. In the proposed model, taking inspiration from [14], [21], we introduce a multi-objective function rather than a single function as used in [14], [21]. This is achieved by incorporating the number of active switches, along with the number of active links. The objective is to maximize network utility while considering constraints related to link utilization, bandwidth, and traffic volume on the network links. By considering multiple objectives, our model aims to achieve a more comprehensive optimization of the network power consumption. In this setting network utility is defined as the overall satisfaction of users with respect to the demands they place on the network. Parameters of the DCN model used by the ILP are summarized in Table II:

The optimal configuration of active links and switches, that achieves the desired network utility, while minimizing the

Table I
FLOW AGGREGATION METHODS FOR ENERGY EFFICIENCY.

Study	Experiments				Objective	QoS	SDN
	Environment	Traffic	Topology	Controller			
Elastic Tree [17].	Test-bed	R	Fat-Tree	NOX	Link	-	√
CARPO [18].	Test-bed	R	Fat-Tree	-	Link	√	-
NetFPGA OpenFlow-based Platform [12].	Test-bed	R & A	Fat-Tree	NOX	Switch & Link	-	√
MTSDPFPR [19].	Mininet	R	GEANT	Floodlight	Link	√	√
Aggregation Strategies [20].	FNSS & Python	A	Fat-Tree	-	Link	-	√
OSC [12].	Test-bed	A	-	NOX	switch & Link	-	√
FPLF [14].	Mininet	A	Fat-Tree	POX	Link	√	√

Table II
PARAMETERS OF THE FLOW AGGREGATION MODEL.

Parameters	Definitions
$\mathbb{F}$	Set of flows, where a flow $f = \big(f.S_r, f.D_s, \lambda_f\big) \in \mathbb{F}$ is represented by source $f.S_r \in \mathbb{S}$, destination $f.D_s \in \mathbb{S}$, and bit rate $\lambda_f \in \mathbb{N}$
ℓ_i	$\begin{cases} 1, & \text{if switch } s_i \in \mathbb{S} \text{ is active} \\ 0, & \text{otherwise} \end{cases}$
L_{ij}	$\begin{cases} 1, & \text{if link } e_{ij} \in \mathbb{E} \text{ is active} \\ 0, & \text{otherwise} \end{cases}$
$FR(f,i,j)$	$\begin{cases} 1, & \text{if flow } f \in \mathbb{F} \text{ passes through link } e_{ij} \in \mathbb{E} \\ 0, & \text{otherwise} \end{cases}$
$BW_{ij} \in \mathbb{N}$	Bandwidth of link e_{ij}
$T_{ij} \in \mathbb{N}$	Traffic volume over e_{ij}

power consumption is determined by the ILP in (2).

$$\min : \sum_{i=1}^{n}\sum_{j=1}^{n} L_{ij} + \sum_{i=1}^{n} \ell_i. \tag{2}$$

This objective function is subject to the following constraints:

1) Links and traffic correlation constraint.

$$\frac{T_{ij}}{BW_{ij}} \leq L_{ij}, \quad \forall e_{ij} \in \mathbb{E}.$$

A link is not activated unless at least one flow passes through it.

2) Links and flows correlation constraint.

$$FR(f,i,j) \leq L_{ij}, \quad \forall f \in \mathbb{F},\ \forall e_{ij} \in \mathbb{E}.$$

Flows can only pass through active links.

3) Utility constraint.

$$\sum_{f \in \mathbb{F}} FR(f,i,j) \cdot \lambda_f \leq BW_{ij} - T_{ij}, \quad \forall e_{ij} \in \mathbb{E}$$

The total packet rate of all flows passing through a link does not exceed the available bandwidth of that link.

4) Path conservation constraint.

$$\sum_{i=1}^{n} FR(f, f.S_r, i) = 1,\ \forall f \in \mathbb{F},$$

$$\sum_{i=1}^{n} FR(f, i, f.D_s) = 1,\ \forall f \in \mathbb{F},$$

Every flow has a unique source $f.S_r$ and destination $f.D_s$.

5) Flow conservation constraint.

$$\sum_{\substack{i=1 \\ i \neq f.S_r}}^{n} FR(f,i,j) = \sum_{\substack{i=1 \\ i \neq f.D_s}}^{n} FR(f,j,i)\,, \qquad \forall f \in \mathbb{F},\ \forall j \in \mathbb{S}.$$

A flow entering a node is equal to the flow leaving the node for all intermediate nodes.

6) Network connectivity constraint.

$$L_{ij} \leqslant \ell_i,\ L_{ij} \leqslant \ell_j, \quad \forall e_{ij} \in \mathbb{E}.$$

Each active link enforces the activation of the corresponding switches to maintain the connectivity of the network graph.

Solving the ILP model with these constraints results in an optimal flow aggregation policy that minimizes power consumption.

It is worth mentioning that the study assumes switches can turn on or enter sleep mode based on local traffic states, using Wake-on-Arrival (WoA) to wake up the switch when needed for forwarding packets and Sleep-on-Idle (SoI) technique for switches to save power when idle, without considering the transition time in the evaluation [24].

B. Flow Scheduling Techniques

Since the SDN controller maintains a global view of the underlay DCN infrastructure, it can calculate deadlines for flows and their size. This ability has motivated the development of new *scheduling algorithms* to manage the transmission of flows through a sequence of queues. These algorithms send the flows sequentially. This allows the flows to monopolise all the links of the path they traverse, using their full capacity, subject to the deadline and flow-size constraints. Fig. 1b shows how three flows are scheduled in a queue for transmission with a full bandwidth. A disadvantage is that these techniques are not appropriate for time-sensitive traffic (i.e., video streaming and VoIP [25]). Flows with higher priorities can be preemptively routed along the paths of other flows with lower priorities. Coupled with this, some applications in DCNs might not require large bandwidth, and be can slow, and thus not saturate the link capacity. Consequently, the link will be underutilized.

1) Methods: To avoid collisions and to achieve efficient power usage in DCNs, the authors in [26] proposed a technique that combined flow preemption and energy-aware routing to reduce energy consumption. Flows were divided into two lists:

Table III
FLOW SCHEDULING METHODS FOR ENERGY EFFICIENCY.

Study	Experiments				Objective	QoS	SDN
	Environment	Traffic	Topology	Controller			
Preemptive Flow [26].	NS-3	A	Fat-Tree	-	switch	√	-
Green Data Center [27].	-	A	B-Cube & Fat-Tree	-	switch	√	√
BEERS-1 [28].	OMNeT++	A	Fat-Tree & BCube	-	switch	√	√
Willow [24].	-	A	Fat-Tree	-	switch	√	√
BEERS-2 [29].	OMNeT++	A	Fat-Tree & BCube	-	switch	√	√
FLOWP [30].	OPNET	A	Fat-Tree	-	switch	√	√

a sending list and a waiting list. When a new flow entered the DCN, the algorithm checked the flow's priority based on its size. The flow either interrupted an ongoing data transfer and was directly routed to the destination, or was moved to the waiting list based on its assigned priority. Simulations were used to evaluate the performance of their technique and to compare it to other state-of-the-art techniques, such as ECMP. They used the ns-3 network simulator and a Fat-Tree topology. Results suggest that it can be a practical and effective way to make DCNs more energy-efficient.

The authors of [27] were motivated by the importance of implementing exclusion flow routing techniques on different topologies. They proposed a scheduling algorithm based on the priorities of flows, which assigned higher scheduling priority to smaller flow sizes, as in [26]. Experiments were conducted on two types of DCN topologies, namely BCube and Fat-Tree, using OpenFlow as the southbound API. Two metrics were used to evaluate the algorithm's performance: the flow arrival rate and the amount of power saved. The results showed an improvement in the utilization ratio of active links, leading to a reduction in power consumption in both topologies, along with the elimination of traffic congestion on active links.

The authors in [30] were motivated by the need to find an optimal subset to optimize power usage. A convex objective function was used to model energy consumption. Two strategies were pursued, an optimal combinatorial algorithm which was composed of two components (Most-Critical-First and Shortest Path (MCF-SP)) and a Random Scheduler (RS). MCF-SP managed flow scheduling based on the weight and the deadline of the flows. All the flows were sorted according to an Earliest Deadline First (EDF) policy. Power usage was optimized by minimizing the transmission rate of the flows per unit of time. By modeling the problem as a convex optimization problem the authors showed that MCF-SP found the optimal solution to the Deadline-Constrained Flow Scheduling (DCFS) problem under the assumption that flows were routed exclusively through a virtual circuit. Conversely, the RS involved relaxing an NP-hard problem, the Deadline-Constrained Flow Scheduling and Routing (DCFSR) problem. Relaxation consisted of finding an approximation based on a Fractional Multi-Commodity Flow (F-MCF) problem. The power optimization was based on two criteria: a minimum transmission rate criteria for the flows and a usage criteria for the links. The evaluation procedure was conducted using Python, however, the description of the set-up makes comprehensive understanding and reconstruction of the results challenging. Because the aggregation method was not suitable for network-limited flows, the application generated traffic at a high bit rate, and the flow's throughput depended on the network capacity of the routing path. To overcome this challenge a flow scheduling approach named "Willow" was proposed in [24], which took into consideration both the number of switches involved and the durations of their frame working times. A greedy approximate algorithm was designed that scheduled flows in a real-time manner. The proposed algorithm achieved a network energy consumption saving of 60 % of network energy compared to the conventional ECMP scheduling approach.

To overcome the problem of greed in flow selection when finding an energy-efficient path in [30], the authors of [28] proposed an approach that aggregated the flows with a similar deadline into a harmonic flow set, and scheduled them with higher priority, resulting in increased link utilization. The resulting scheduling algorithm was named "BEERS". It ran as a model in the SDN controller. Simulations were run using the OMNeT++ simulator, and results showed improvements in the link utilization and the energy consumption compared with the Exclusive Routing (EXR) algorithm. However, since all the flows competed for links in different periods, it was challenging to form a harmonic flow set at certain points in time, which posed a challenge for the algorithm. The authors extended the BEERs approach and conducted extensive experiments with two types of topology [29]. The results showed that their algorithm could reduce overall energy consumption with respect to traffic volume, and that it could also reduce the average flow completion time.

Conventional methods for reducing power consumption, such as turning off unused switches, can negatively impact network performance. To address this issue, the authors in [31] proposed a dynamic flow scheduling algorithm that balanced the workload on network switches to reduce power consumption. The algorithm considered the flow size, a threshold value that controlled the time delay. The algorithm is evaluated using a simulation-based approach, using OPNET, and the results showed that the algorithm could be an effective solution for reducing power consumption in DCNs without sacrificing performance. Table III summarizes the flow scheduling methods according to the adopted evaluation criteria and the main objectives.

2) Formulation: Similar to the approach in Section II-A2, we present the objective function and constraints that mathematically formulate an ILP model that optimizes power consumption in DCNs using flow scheduling techniques.

The goal we seek to achieve with the objective function

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Table IV
PARAMETERS OF THE FLOW SCHEDULING MODEL.

Parameters	Definitions
L_{ijk}	$\begin{cases} 1, & \text{if link } e_{ij} \in \mathbb{E} \text{ is active during timeslot } k \\ 0, & \text{otherwise} \end{cases}$
$FR(f,i,j,k)$	$\begin{cases} 1, & \text{if flow } f \in \mathbb{F} \text{ is scheduled on link } e_{ij} \in \mathbb{E} \text{ during timeslot } k. \\ 0, & \text{otherwise} \end{cases}$
$C_f \in \mathbb{N}$	Bandwidth required by flow f in Mbps
$La_f \in \mathbb{N}$	Latency tolerance of flow f in microseconds
$\alpha_f \in \mathbb{N}$	Starting timeslot of flow f
$\omega_f \in \mathbb{N}$	Ending timeslot of flow f, $\alpha_f \leq \omega_f$
$la_{ijk} \in \mathbb{N}$	Latency of link e_{ij} during timeslot k
$p_{ij} \in \mathbb{N}$	Power consumption of link e_{ij} in watts

in (3) is to minimize power consumption while maintaining network performance metrics. Prior to defining the objective function we define the role of its constituent components in Table IV.

The objective function computes a weighted sum of the variables L_{ijk} for all active time slots and the power consumption p_{ij} for each link.

$$\min : \sum_{i=1}^{n} \sum_{j=1}^{n} \left(p_{ij} \cdot \sum_{k} L_{ijk} \right) \tag{3}$$

The above objective function is subject to the following constraints to guarantee network performance: bandwidth, latency, etc.

1) Bandwidth constraint.

$$\sum_{f \in \mathbb{F}} C_f \cdot FR(f,i,j,k) \leq BW_{ij}, \quad \forall e_{ij} \in \mathbb{E},\ \forall k.$$

The total bandwidth usage of each link should not exceed its maximum bandwidth capacity BW_{ij} during any timeslot k.

2) Latency constraint.

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k} la_{ijk} \cdot FR(f,i,j,k) \leq La_f, \quad \forall f \in \mathbb{F}.$$

The sum of the latencies of all links used by a flow f must not exceed its latency tolerance La_f.

3) Workload constraint.

$$\sum_{f \in \mathbb{F}} FR(f,i,j,k) \leq 1, \quad \forall e_{ij} \in \mathbb{E},\ \forall k.$$

Each timeslot k can have at most one flow scheduled on a link e_{ij}.

4) Flow activation constraint.

$$FR(f,i,j,k) = 0, \quad \forall f \in \mathbb{F},\ \forall e_{ij} \in \mathbb{E},\ \forall k \notin [\alpha_f, \omega_f].$$

The decision variables $FR(f,i,j,k)$ are set to 0 for each flow f outside of its specified time interval between α_f and ω_f. α_f represents the timeslot at which the flow f is allowed to start its transmission. ω_f represents the timeslot by which the flow f must be completely served or finished with its transmission.

5) Links and flows correlation constraint.

$$FR(f,i,j,k) \leq L_{ijk}, \quad \forall f \in \mathbb{F},\ \forall e_{ij} \in \mathbb{E},\ \forall k.$$

Flows can only pass through active links, enforcing L_{ijk} to be in the ON state.

Similarly, the Path conservation constraint and the Flow conservation constraint from Section II-A2 have to be adapted, simply by quantifying over the timeslots k.

III. OPEN ISSUES AND DISCUSSION

Although the SDN paradigm presented a solution to many existing network issues such as those related to power consumption, SDN-based DCN power consumption still needs more investigation and verification under various workload circumstances. It is possible that implementing power optimization approaches based on SDN can result in an increase in the *response time* of the controller. This is because the controller has to continuously monitor the network and to make decisions on how to optimize power consumption while maintaining network performance. This overhead may cause delays in the controller's response time.

Moreover, finding the *optimal subset* of active links and switches can be an expensive process that may require significant *computational resources*. This can lead to a loss of performance in a DCN since the resources used for optimization cannot be used for other critical network functions. Furthermore, some approaches require the use of *heuristics or approximation algorithms*, such as the methods in Sections II-A1 and II-B1, which can typically provide only suboptimal solutions. Therefore, before implementing power optimization approaches based on SDN, it is important to carefully evaluate the potential trade-offs between power consumption, network performance, and computational resources. Further investigation may be required to identify the optimal balance between power optimization and network performance in a particular DCN. Further research which take these variables into account, will need to be undertaken. Moreover, there are several potential advantages when implementing a multiple SDN controllers in DCN, which is discussed in the next section.

A. Multiple Controller SDN

Using multiple controllers can potentially help mitigate the problem of increased response time in power optimization approaches based on SDN. By distributing the workload across multiple controllers, the overall response time can be reduced, improving network performance. Moreover, multiple controllers can potentially improve the efficiency of finding the optimal subset of active links and switches. Different controllers can be responsible for different parts of the network, and they can work together to find the best solution. This can help to reduce the computational demand and improve the speed of optimization. However, the synchronization of multiple controllers in an SDN environment can be achieved through various methods, such as: (1) *Consistency Protocols* ensure that all controllers have the same view of the network. (2) *Event Notifications* are used by controllers in order to communicate with each other. For example, the OpenDaylight (ODL) controller provides a notification service that allows controllers to subscribe to events and to receive notifications when the state of the network changes. (3) *Replication*: Controllers can replicate/duplicate their state and share this copy with other controllers in the network. For example, the Floodlight controller uses a master-slave replication mechanism to synchronize the state of multiple controllers. By using one or more of these methods, multiple controllers in an SDN environment can synchronize their work and ensure the efficient operation of the network. Therefore, when considering the use of multiple controllers, it is important to carefully evaluate the potential benefits and drawbacks, and design the network architecture and control algorithms accordingly.

B. Machine Learning-Based Approaches

Machine Learning (ML) is a promising approach for solving a wide range of computer networks problems. ML-based techniques can be used to optimize power consumption in SD-DCN. By analyzing network traffic patterns and predicting network demand, ML algorithms can help SDN controllers make real-time adjustments and reconfigure the network to optimize the energy usage. One approach that has been explored in research is using ML to *predict the network demand* for different time periods, such as hourly or daily intervals [32]. Based on these predictions, the SDN controller can adjust the routing of network traffic to reduce power consumption during periods of lower demand. Other ML algorithms can be used to *analyze the behavior of individual network components*, such as switches or servers, to identify patterns that indicate when these components are not being used efficiently [33]. This information can then be used by the SDN controller to adjust network configurations and optimize power usage.

Finally, using ML algorithms to classify network traffic in real-time, SDN controllers can make more informed decisions about network traffic routing and resource allocation, leading to improved network performance and efficiency besides efficient power usage [34]. Overall, ML-based approaches have the potential to significantly reduce power consumption in DCNs, which is an important consideration for organizations looking to improve their energy efficiency and to reduce their carbon footprint.

IV. Conclusion

The escalating power usage in DCNs has become a global concern. Energy optimization techniques that are actively researched are notably scheduling and flow aggregation methods. This paper addresses a literature gap by reviewing cutting-edge SDN-based approaches for traffic scheduling and aggregation in DCNs and analyzing their pros and cons. It highlights the limitations of multi-controller SDN solutions due to performance constraints. Future research avenues include leveraging machine learning to optimize traffic algorithms and exploring hybrid solutions combining advanced scheduling, aggregation techniques, and multi-controller setups.

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