Distributed Multi Criteria Routed for MPLS-TE Based on Machine Learning: Concept and Applications

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Abstract —MPLS-TE Networks are complex interacting systems, providers integrate absolutely the forwarding equivalent class involving in the dynamic routing algorithm "Dynamic Multi Criteria Routing", especially with network services such as an IPtv, a VPNs or a VoIP with the several types of video streaming and similar user applications, making its flagship technologies of tomorrow. Machine learning is very compatible for this kind of networks. In this paper, we first review how the main machine learning concepts can be integrated in communication networks and discuss concepts, supervised and unsupervised model suitable to the network, data and management strategies, and creating a new architecture of network controls and management tools. We then describe case studies networking in detail, anticipate anomalies at multiple network layers, covering predictive maintenance, descriptive network topology management, capacity optimization. Finally, we prove the importance of this work, and guess an overview of intelligent dynamic networks.

Index Terms—ML, MPLS, big data, routing, quality of service, DMCR

I. Introduction

Traffic flow through the network backbones operator is mainly transmitted the content with a "best effort" approach. However, part of the delivered traffic should be routed through an insured path, for a moment, it defines the treatment criteria such as bandwidth, jitter and delay. Multiprotocol label switching (MPLS) with Traffic Engineering (TE) can include SLA requirements and, in fact, primarily works like a backbone network protocol for management and routing [1], [2].

MPLS is a new technology and standardized by IETF which conforms to both Layer 2 and Layer 3 using labels (or tags) for differentiation and routing functions of packets in the backbone network. with Traffic Engineering (TE) techniques, MPLS can offer more flexiblity way, the best exploitation of resources, anticipate needs of a user demand and take into account network constraints change [3], [4].

In this environment, the algorithm of routing is an decisive choice, because the TE optimization requires a path selection for routing with taking in consideration some constraints criteria. In principle, for each incoming flow traffic, the network should choose the path correlate with the requested quality of service [5]. Unfortunately, this operation leads to congestion problem. Thus, the new generation of algorithms has been developed with a good balance between the QoS requirements (least bandwidth...) and path computing speed (higher path selection rate) [6], [7].

The main objective searches for the path load balance “average expectation load”, in order to explore the max residual bandwidth of network links, and avoiding “critical” links. Dynamic Online Routing Algorithm (DORA) [8], Stochastic Estimator Learning Automata (SELA) [9], Minimum Interference Routing Algorithm (MIRA) [10], DMCR_MPLS and other similar algorithms use the same concept of Traffic Engineering to reach out this goal.

The principal objective of the traditional IP network system, like OSPF and RIP of the IGP (Interior Gateway Protocol), BGP4 of the EGP (Exterior Gateway Protocol), primarily assures to provide data accessibility services, however the Quality of Service (QoS) is one of the most important challenge what the Next Generation Network (NGN) must face the ability to regulate the whole network's resources. These routing algorithms forward packets based on network status to choose the shortest path, which usually result in network disruption. The Traffic Engineering (TE) has been proposed, to solve this problem of resources exploration caused by the unbalanced distribution of the load. As an advanced backbone network for transmission of NGN, MPLS-TE is an efficient mechanism to guarantee the QoS [11].

MPLS relies on labels switching mechanisms in order to reduce the routing cost of network and giving it a better performance, a higher scalability and a greater flexibility in network restoration services. MPLS is a switching technology using labels. In MPLS backbone, incoming packets are assigned a "label" by a "LER (label edge router)" according to their forwarding equivalence class (FEC). Packets are forwarded through a "label switch path (LSP)" and each "LSR (label switch router)" should forwarding decisions based solely on the contents of this label, without dealing its IP address. At each hop, the LSR changes the received label and applies a new label for the next hop and so on, until the exit of backbone. These established paths, Label Switch Paths (LSPs) can guarantee some levels of service, to avoid the network congestion using VPNs virtual private networks. This technology is hugely appreciated by the majority of Internet service providers as well as by some major companies, can integrate the network services. In the

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other side, These new services increase the complexity of management and will obviously encourage researches of these different networks. In terms of QoS, MPLS insures as well as a better management of routing, switching and transfer packages [12]. (See Fig. 1)

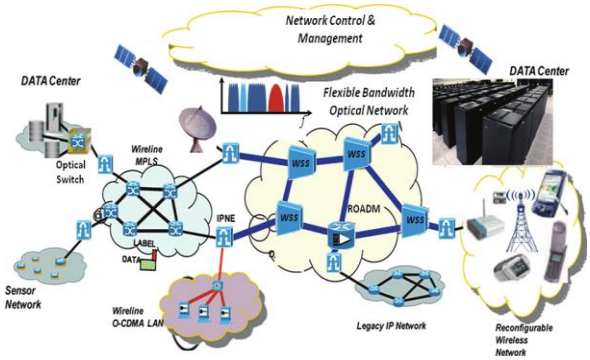

Fig. 1. Heterogeneous network architecture using MPLS

Furthermore, MPLS is based on four great aspects to improve and solve many problems outlined above:

- The path defined in advance that will take data or types of sent data through the network (Traffic Engineering).
- Internet service providers can create tunnels VPNs (Virtual Private Network), and solving problems related to their multiplication.
- Interoperability: associated label is independent from several technologies support like IPv6, IPv4 layer 3, and Ethernet, Token Ring, and so on.
- Creates a better interaction between the traditional routing protocols such as OSPF (Open Shortest Path First) and BGP (Border Gateway Protocol).

In general, the architecture is based on MPLS mechanisms switching labels linking Layer 2 of the OSI model (switching) with the layer 3 of the OSI model (routing). Moreover, switching in the layer 2 is independent of the used technology. The mechanisms of MPLS-TE include multi criteria, such as path selection, residual bandwidth, load balancing and second path. MPLS uses LSP (Label Switched Path), which are labels pre-calculated path, to forward the IP data received through the network. The choice of LSP is the first step to implement MPLS-TE [12].

II. Machine Learning Techniques Applied to Communication Network

In this section, we review how main concepts of ML can apply to communication networks in order to attempt network automation [13].

A. Data

The first element is the data collection since the data is the mainly source of information, called the nerve of war, on which the life cycle of ML layer attaches. Next element is the different algorithms that can be used to train the data and learn the model and extract the relevant information from raw data collected by the infrastructure setting in place. Last one is applications cases that exploit this information to solve network problems and provide added service [14].

Many data sources can be exploited to get information about every network component, from the end user through the communication channels to the service operator, usage behaviors, topology, and business context. the performance of the channel is characterized by bit error rate, transmit and received power and signal-to-noise ratio. To compute the performance of the IP layer is measured by latency, error rate, throughput, bandwidth and jitter.

With a new generation networking and every time described data is collected, it is very important to notice also a timestamp affected with it. For define a “snapshot” that contains Data collected during a common time interval. Moreover, chronological order of data is useful for assessing "time-series" trends. Communication networks tend widely to generate a several variety of data.

In addition, the velocity frequency of each source and its average time of storage vary according to every snapshot and the resources capacity, after a large data volume, is collected from operational communication, this last is referred as “Big Data” and characterized by volume, velocity, and variety. In ML, the labels are used to train supervised ML algorithms. For assessing the data veracity, is very interesting to test the performance of trained ML models.

At every time, a supervised learning assigns a label that indicates the state of a network element (“normal”, “abnormal”), we have to define the kind of collection such as batch or stream processing data. Batch when the data is storing in the data lake, streaming when the data is intercepted at a real time for processing. It is too hard to automate the collection of labels at live systems [15].

B. Algorithm

At the port of algorithm, we will start with tasks that can be applied with an access as “read-only” in MPLS operations networks, such as linear or logistic regression, classification in application scenarios. and how machines can learn how to act on a network in the Software-Defined Networking (SDN) will act in the automation context that is offered by a feedback closed-loop, we will prove how each technique can be enforce with different algorithms. The popular ML frameworks like Spark MLlib, R, SciPy, TensorFlow, SciKitLearn and others [16]. (See Fig. 2)

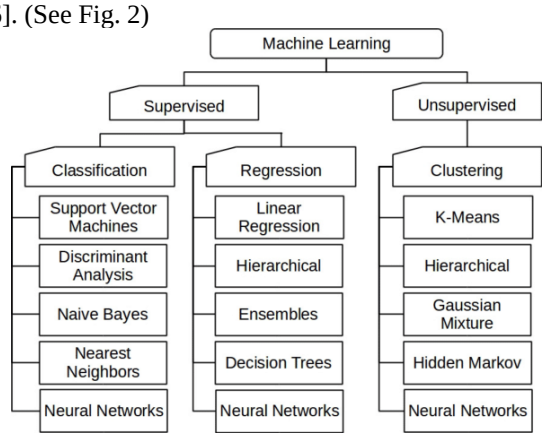

Fig. 2. Machine learning and its classifications

In general, ML algorithms contain two broad categories, supervised and unsupervised learning according to model kind implemented in training.

For unsupervised ML involves three components:

- Dataset X,
- Model M(x, θ),
- Cost function C(x, M(x, θ)).

The vector x represents a "snapshot" of the system under study.

$$M(x, \theta) \text{ --Training -->} M(x, \theta^*)$$

In supervised ML, the data scientist adds an additional form, is the label that indicates the true nature of the system under study [17], [18].

This transforms a raw dataset X into a dataset labeled Xy where y describe the label (s) assigned to each x.

The additional label information can be extended in the cost function C(y, x,M(x, θ)). The minimization of Co will favor parameters that generate the correct answer for y. Thus, in supervised ML, the machine learning can predict labels y from x, such that:

$$\text{Lim } |X| \to \infty M(x, \theta^*) \approx P(y/x)$$

1) labels can define the true state of a network instance ("normal state", "abnormal state"…)

2) Regression-Data-Driven Network Optimizations: the main function is the reliability machine to predict a numerical value given from model M(x, θ) which θ represents classic network parameters (bandwidth, topology, , etc.) and x represents historical data (business data, abnormal state, etc.),

3) Regression-Prediction: it can anticipate future events from trends given by historical data, like bandwidth congestion, device failures or network capacity exhaust [19].

4) Classification of Network Events: this type of algorithm can be used to characterize recognize patterns or network properties associated with different types of network events. It is based on classification of image recognition given the properties of ML by using network "snapshots" instead of photographs.

5) Detection of Network Anomalies: In anomaly detection, the task is to identify abnormal or atypical elements xi among a dataset X.

6) Learning to Take Actions: we have discussed supervised and unsupervised ML algorithms that can produce an action from "read-only" datasets for network automation [20], [21]. (See Fig. 3)

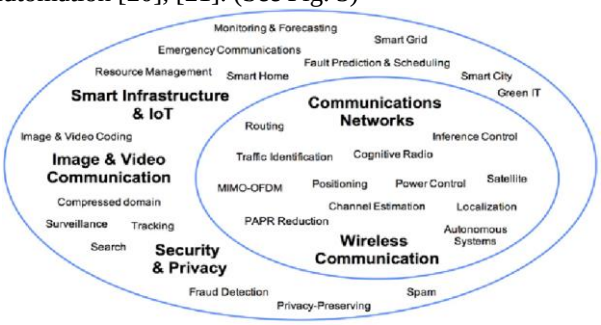

Fig. 3. Convergence of ML and communication network

C. Infrastructure

Infrastructure is indispensable to handle the large volume, variety, and velocity of the "Big data" (see next section) in order to exploit synergies of ML. Large data volumes require two main techniques distributed storage and parallel computing rallied in a computer cluster. Wide variety requires a "Resource Adapter" that is an abstraction layer between the raw inputs from several sources and the ML algorithms. Furthermore, it requires an efficient framework to manage and process batches of data. This is commonly done with the software tools Apache Hadoop and Apache Spark. Finally, fast velocity from several sources requires ingestion capabilities (data streaming). This can be applied by tools like Apache Sqoop or Kafka [22], [23]. (See Fig. 4)

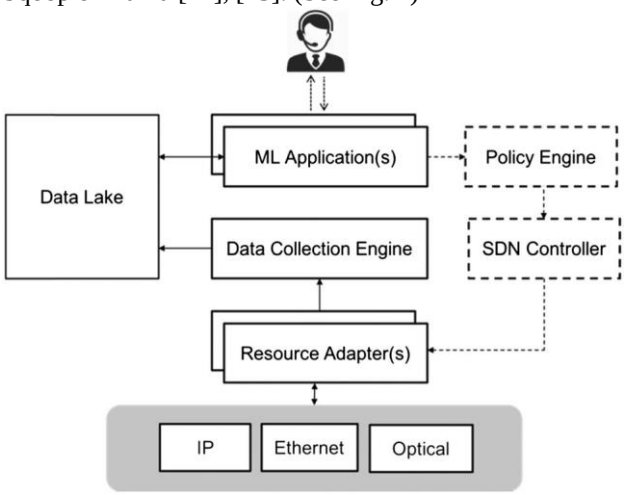

Fig. 4. Infrastructure using ML applications in communication networks MPLS

III. Approaches in Big Data Analytics for Quality of Service

Big data analytics is one of the most advanced technologies that hold the huge volume of data without any problem. It has many features which become by finding the information in the social media like preferences and product perception of their consumers, product companies and retail organizations are planning their production. The huge data set which stores huge volume of data in the form of historical the data such as previous detail of the system [24].

Ultra-high-dimensional data models can be created to profile stream data accurately online, which it helps predict and give solutions in real time. Big data technologies like the Hadoop ecosystem and stream processing can store and analyze large heterogeneous datasets at a high speed, transforming security analytics in term of frame work in the Hadoop that will analyze the information in the network and has got the efficient algorithm in the form of a set of rules and the stream regulations. It controls the data routing and the nodes positions by comparing the models of data sets in the data bases that can be processed by the big data analytical [25].

Map Reduce is a frame work of Hadoop and it has big data sets that are stored and processed by big data

analytical engine with using a set of algorithms in the form of clustering and it can be computed by using the parallel processing technique. A program is composed of Map procedure (method) that performs filtering and sorting (such as sorting students by name or number) and a Reduce() method that performs a summary operation (such as counting the number of students that have the same family name) [26], [27]. The Map Reduce System orchestrates the processing on marshalling the distributed servers, running the various tasks in parallel, managing all communications and data transfers between the various parts of the system, and providing for redundancy and fault tolerance. Map Reduce is a processing technique and a program model for distributed computing based on java. The Map Reduce algorithm contains two important tasks, namely Map and Reduce. Secondly, reduce task, which takes the output from a map as an input and combines those data tuples into a smaller set of tuples [28]. (See Fig. 5)

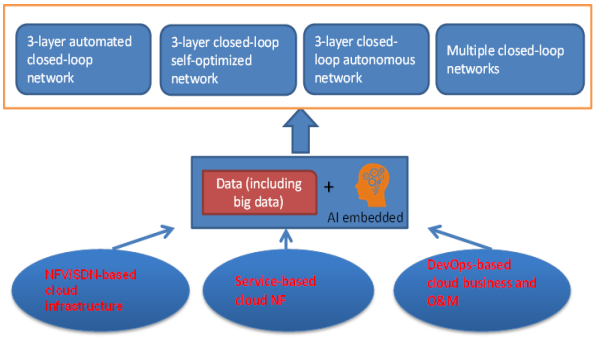

Fig. 5. Big data and automation networks

Based on the survey of the papers, the Map Reduce Algorithm uses the data sets in the input of the algorithms like a neural algorithm, K-Mean algorithms, clustering Algorithms and classification in data sets. Many research papers are improved the QoS in the network by using the Big data analytics scheme which has the efficient and effective process of holding the data sets [28].

IV. Distributed Multi Criteria Distributed Routing

A. Cirteria Functions

Vector Algorithm, is also known as the Bellman-Ford algorithm after its inventors: each router updates its routing table step by step exchanging the routing information (distance vector) with its direct neighbors. A vector is a number referenced by two factors: the magnitude and direction. In a network, you could say it that has a cost and a destination [29].

Sending vector distance, to neighbors routers, is done periodically, the exchange of information between the routers to update their routing tables based on a received data and then the network converges step by step to stabilize. if a router stops sending distance vector is considered in a failure state, and will have an infinite cost[30].

In DV, each node maintains its Distance Table. The distance table has one row for each possible destination and one column for each neighbor.

These entries are calculated through the exchange of information between neighbors. More specifically:

"E emitter node, that is interested in routing to destination D through node neighbor I. Node E's distance table entry, Ce(D;I) is the sum of the cost of the direct one-hop link between E and D, c(E;I) and a neighbor I is currently known as the minimum cost path from itself (I) to D . That is:

$$Cx(Y;I) = c(E;I) + \min_{\omega}\{CI(D;\omega)\}$$

The $\min_{\omega}$ term in the equation is taken over all of I's directly attached neighbors ...[30]

Multicritria distributed methods have been designed to help avoiding a wide variety of problems in many different applications such as streaming, real time, transportation, etc. For purpose of simplicity and explanation, this work based on one particular Multicritria distributed method: Normalized Weighted Function (NWF). However, other complex MCD methods can be used, the NWF method is based on normalizing criteria values (QoS parameter) and using weights of importance varies between 0 et 1, with a sum of weight is one.

During our work, we will treat three criteria:

- Jitter:

  $f1: E_e(d;i) = E(e;i) + \min_{\upsilon}\{E_i(d;\upsilon)\}$

  Where Ex(Y;N) is the total energy consumption from e to d destination via the direct neighbors of e, the node i, E(e;i) is the energy consumption by using a direct link from node e to node i, and $\min_{\upsilon}\{Ei(d;\upsilon)\}$ gives node i is the path of minimum energy to destination d. All neighboring nodes directly linked node N is denoted by υ.

Similarly, the objective functions for latency and Bit Error Rate (Quality), were formulated as follows:

- Delay,

  f_2:$De(d;i) = D(e;i) + \min_{\upsilon}\{D_i(d;\upsilon)\}$

- Bit Error Rate (Quality),

  f_3: $R_e(d;i) = 1 - ((1- R(e;i)) - (1 - \min_{\upsilon}\{R_i(d;\upsilon)\}))$

B. Normalized Weighted Function

NWF is used as a means of evaluation criteria, that takes into considering the need of users and the application preferences. This function allows us to have cost standardized, between 0 and 1. The NWAUF method consists of five steps. They are:

1) For each criterion, find the variation of link function values. Define: fi,min=min{fij ; j = 1; 2; … ; n},

for each criterion f_i; i = 1; 2; … ; k

and fi,max =max{f_{ij}; j = 1; 2; …. ; n},

for each criterion f_i; i = 1; 2; …; k. Note that $f_{i,min}$ and $f_{i,max}$ can be defined by the decision-maker to be values other than those found above.

2) Normalize each f_i to be maximized according to:

$f_{ij}'=(f_{ij} - f_{imin})/(f_{imax} - f_{imin})$; $0 < f_{ij} < 1$ for all i and j

3) Assess weights of importance for each criterion $\omega_1;\ldots;\omega_k$, where:

$\sum k_i=1$, $\omega_i = 1$ and $\omega_i > 0$ for all i

4) Calculate the utility U(aj) for each link aj :

$U(aj)= \sum k_{i=1} \ \omega_i f_{ij}$ for all j = 1; 2; ⋯n

5) Rank alternatives in descending order of U(aj). The link with the highest U is the best hop.

One or more measured criteria can be associated with each link in a route. The Multiple Criteria Routing measurement is a function of all of the links multi-criteria measurements that compose the route.

MCR implements several constraints on the quality of service, taking into account the requirements of each stream, providing multiple paths, which allows the passage through the backup paths: traffic engineering (TE). Hence the load balance network with an optimized management.

A new advanced routing algorithm is proposed in this paper, which is called the Distributed Multi Criteria Routing (DMCR). For optional paths of each ingress-egress pair, algorithm uses a learning mechanism, combines offline and online routing, and chooses the LSP in terms of the reject message and the residual bandwidth and machine learning analysis according to the batch and streaming data of candidate paths by calculating the maximum flow of network. Then it sorts all possible paths according to this principle, and gives priority to the path in the front. (See Fig. 6)

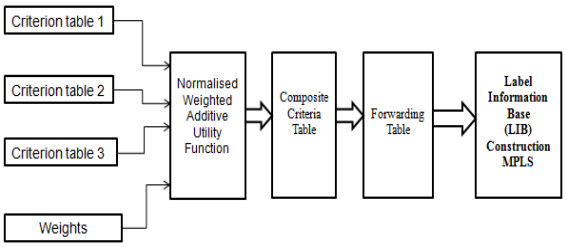

Fig. 6. DMCR algorithm within each node MPLS with closed-loop Machine learning.

V. Conclusion

Classical networks are providing from widely static operational and management services that decrease their reliability and efficiency both technically and economically.

In this paper, we proved how to integrate the Machine learning concept which offers techniques to achieve the automated network behavior and then will transform today static network into a dynamic, in order to build a new architecture of management .

We have discussed several aspects such as algorithm choice, storage and representation aspects, model management: architecture, then we presented its solutions such as proactively detecting soft failures.

Our goal is a compatible platform for end-to-end dynamic network in order to improve whether network resource utilization or operational efficient. Open data gives "read only" access to network data for have a dynamic environment piloted by data analytics and artificial intelligence.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The first author designed the interference management technics, simulation results and wrote the paper. All authors had approved and analyzed the final results and the final version.

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