A Learning Automata-based Algorithm for Energy-efficient Elastic Optical Networks

Georgia A. Beletsioti[1][a], Georgios I. Papadimitriou[1][b], Petros Nicopolitidis[1][c], Emmanouel Varvarigos[2][d] and Stathis Mavridopoulos[1][e]

[1]Department of Informatics, Aristotle University of Thessaloniki, Thessaloniki, GR-54124, Greece

[2]School of Electrical and Computer Engineering, National Technical University of Athens, Athens, GR-15780, Greece

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Abstract: Efficient use of available bandwidth plays an important role in performance enhancement due to the wide penetration of high-bandwidth demanding services. The flexible nature of elastic optical networks (EONs) effectively uses spectral resources for communication by allocating the minimum required bandwidth to customer requirements. Since the energy consumption of such networks scales with the magnitude of bandwidth demand, many studies have addressed the issue of energy wastage in optical networks. Learning Automata are Artificial Intelligence tools that have been used in networking algorithms where adaptivity to the characteristics of the network environment can result in a significant increase in network performance. This work introduces a new adaptive power-aware algorithm, which selectively switches off bandwidth variable optical transponders (BVTs) under low utilization scenarios supporting energy efficiency. A novel algorithm which uses LA technology and significantly reduces the total energy consumption, while maintaining low bandwidth blocking probability (BBP), is proposed. LA mechanism applied in this work, aims to find the best number of BVTs to be switched off so as for the BBP not to be affected. Simulation results are presented, which indicate that the proposed algorithm achieves a power saving of up to 50%, compared to non-adaptive solutions.

1 INTRODUCTION

The demand for bandwidth grows exponentially every year, driven by a growing number of global internet users. Furthermore, high capacity-demanding technologies, including autonomous vehicles, the internet of things, high bandwidth enhanced video, and virtual reality, will also drive future needs. According to Cisco, global IP traffic stood at 122 Exabytes in 2017 and it is estimated that these numbers will triple by 2022 (Cisco, 2019).

Elastic optical networks (EON), as a novel concept of WDM networks, are considered the most suitable architecture for backbone and next generation metropolitan networks as they are characterized by high spectral efficiency and adaptability (Jinno, 2017). EONs which are based on orthogonal frequency-division multiplexing (OFDM) (Dao et al., 2018) support lightpaths with different bitrates, exploit the flexible grid technology where the spectrum is split into 25, 12.5 GHz or less slots compared to coarser splitting of 50 GHz or 100 GHz of traditional WDM networks. Hence, the slots are combined to create channels, which are not overlapping due to OFDM's orthogonality capacity, of the desired size using bandwidth what is strictly necessary for the transmission spectrum (Soumplis, 2017).

The energy consumed by ICT (Information and Communication Technology) equipment, which is rapidly expanding (Belkhir and Elmeligi, 2018), (Beletsioti et al., 2016), causes a significant economic and environmental problem. According to European Framework Initiative for Energy and Environmental Efficiency in the ICT Sector, ICTs account for 8-10% of the European electricity consumption and up to 4% of its carbon emissions. Furthermore, the network infrastructure is becoming a large portion of the energy footprint in ICT. Thus, the concept of energy efficient or green networking has been emerged as a research topic. The issue of energy saving in IP Over WDM

[a] https://orcid.org/0000-0002-1895-094X
[b] https://orcid.org/0000-0001-9529-9380
[c] https://orcid.org/0000-0002-5059-3145
[d] https://orcid.org/0000-0002-4942-1362
[e] https://orcid.org/0000-0002-7058-3147

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networks has been extensively studied during the previous years (Shen and Tucker, 2009), (Chabarek et al., 2008), (Melidis et al., 2019), (Dharmaweera et al., 2014).

Various power-efficient algorithms considering the design of IP over EON (Zhu et al., 2019) can be found in the literature. A fairly common, yet effective method of energy saving is the extensive application of optical bypass, reducing thus the number of high energy-consuming optical-electrical-optical (O-E-O) conversions, as the signal can be transported, amplified and switched directly in the optical domain. In (Zhang et al., 2015), energy efficient traffic grooming in IP-over-elastic optical networks taking into account sliceable optical transponders is studied. MILP models among their corresponding heuristics are implemented, for each of three different types of bandwidth variable transponders, and investigated in terms of energy efficiency. Based on traffic and optical grooming methods, Selene heuristic (Kyriakopoulos et al., 2018) is an online algorithm which exploits the innovative Signal Overlap technique for power savings in EONs. The work in (Vizcaíno et al., 2012) is dedicated to the study of energy efficiency in optical transport networks, comparing the performance of an innovative flexible network grid based on Orthogonal Frequency Division Multiplexing (OFDM) with that of Wavelength Division Multiplexing (WDM) with a Single Line Rate (SLR) and a Mixed Line Rate (MLR) operation. Energy-aware heuristic algorithms are proposed for resource allocation both in static (offline) and dynamic (online) scenarios with time-varying demands for the Elastic-bandwidth OFDM-based network and WDM networks (with SLR and MLR). Lopez et al. in (Vizcaino et al., 2012), provides an in depth energy efficient comparison between conventional path protection schemes for fixed-grid (WDM) and flexible-grid (EON) networks.

Besides the above mentioned techniques, a considerable number of published articles pertaining to artificial intelligence (AI) approaches in conjunction with energy efficiency issues in optical networks can be found in the literature (Musumeci et al., 2018), (Mata et al., 2018). Kyriakopoulos et al. in (Kyriakopoulos et al., 2014) propose a heuristic method based on ant colony optimization to reduce network energy footprint by exploiting the basic principles of swarm intelligence for finding the most energy-efficient routes from source to destination nodes. In addition, a multi-objective genetic algorithm is proposed by Fernández et al. in (Fernández et al., 2012) to design virtual topologies in order to reduce both energy consumption and network congestion.

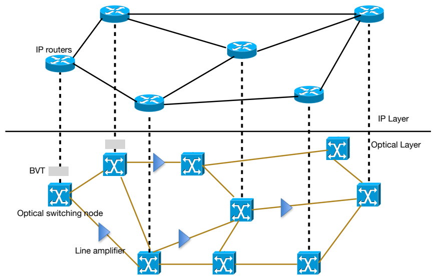


Figure 1: IP-Over-EON Architecture.

2 NETWORK MODEL

2.1 IP Over EON Architecture

A typical IP Over EON architecture, as shown in Fig. 1, is considered. The IP Over EON consist of two layers, the IP and the optical layer. In the IP layer, each node is equipped with a central IP router, while the optical layer consists of the optical switching nodes connected with fiber optic cables. The optical layer offers the link between the IP routers. In each node multiple traffic streams from access network enters the IP router. Each IP router port is connected to the optical switching node through BVTs. At the starting point of the data transmission, BVTs are responsible to convert the electrical flows from the IP layer to optical flows (E/O conversion), then the traffic enters the optical domain and is routed in all optical connections over the optical network. When all optical traffic traveling along the lightpath reaches its destination, the BVTs converts the signal back to electrical (O/E conversion) and finally reaches the end point at the IP layer. Data are then forwarded and handled by the corresponding IP router. Finally, to enable optical signals to travel over long distances, erdium doped fiber amplifiers (EDFAs) are used in fiber optic connections.

2.2 Elastic Optical Transponder Technologies

Two types of transponder technologies according to their sliceability degree can be categorised as follows. **Non-Sliceable BVT.** This type of transponder is designed to provide flexible lightpaths. NS-BVT allows any optical channel with any spectral width and central frequency to be established. NS-BVT has only one slice and it is exclusively used to serve one lightpath, and thus it is called non-sliceable. Due to its high available bandwidth it is offered to serve future demands (i.e 400 Gbps). However, it often suffers from low utilization.

Sliceable BVT. To overcome the above inflexibility of NS-BVT, sliceable BVT were proposed in the literature (Sambo et al., 2017), (Jinno et al., 2012). Unlike NS-BVT, this type of transponder which is also designed to provide flexible lightpaths, allows more than one lightpath to be established in the same transponder. A physical transponder can be logically sliced into multiple sub-transponders, each of which can serve an independent lightpath between source and destination nodes without electric processing at intermediate nodes. As a result, various optical flows can be aggregated into one optical transponder in order to improve its utilization. This feature of S-BVT enables optical grooming (Zhang et al., 2015), which can additionally, significantly improve energy efficiency, since no new transponders required for new connections to be accommodated.

3 POWER CONSUMPTION ANALYSIS

The main components, used in this study, which can influence the amount of power consumption on an IP Over EON are the IP router ports, the S-BVTs and the EDFAs. A 400 Gbps IP router port, which connects the IP router to the BVT is considered. An IP router port consumes 560 W (1) (Zhang et al., 2015). The power consumption of a BVT can be expressed as in (2) according to (Zhang et al., 2015). TR represents the transmission rate of the optical transponder, where in case of a sliceable transponder indicates the sum of transmission rates of all sub-transponders. An additional 20% of power consumption is considered as an overhead contribution for each transponder. Moreover, it is assumed that the energy consumption of the transmitter and the receiver are identical and are equal to half of the power consumption of a transponder. Erbium Doped Fiber Amplifiers are considered as amplifiers in this study. The power of the EDFA is represented in Equation (3), in which X is the spectrum width for amplifying. An inline amplifier is deployed every 80km along the fiber, while a postamplifier as well as a pre amplifier are required at the ends of the fiber link. The total power consumption is calculated by adding the total energy consumption of the BVTs, the EDFAs and the IP router ports (4).

$$PC_{IP} = 560(Watt) \tag{1}$$

$$PC_{BVT} = 1.683 \times TR(Gb/s) + 91.333(Watt) \tag{2}$$

$$PC_{EDFA} = 0.0075 \times X(GHz)(Watt) \tag{3}$$

$$PC_{total} = PC_{IP} + PC_{BVT} + PC_{EDFA}(Watt) \tag{4}$$

4 THE LEARNING ENERGY SAVING ALGORITHM (LESA)

4.1 Learning Automata Mechanism

Learning Automata (LA) are artificial intelligence tools that can be applied to learn the characteristics of a system's environment. One major advantage of LA is that they do not need to have any knowledge of the environment they operate or any analytical knowledge of the task to be optimized. A LA is a finite state machine tool which improves its performance by interacting with the random environment in which it operates. The main purpose of a LA is to find within a set of actions the optimal one, that is the action that causes the minimum average penalty received by the environment (or the maximum average reward received by the environment). The low computational complexity that a LA exhibits enables it to rapidly converge to the best action of the environment with which it interacts.

Figure 2 illustrates the operation of a typical LA, in which there is a set of possible actions $a_1, a_2 ,.., a_M$ as well as the corresponding probabilities p. $P(n) = p_1(n), p_2(n), ..., p_M(n)$ constitutes a vector which represents the probability distribution for M actions at each instant n. It holds that $\sum_{i=1}^{M} p_i(n) = 1$. At first, the LA has no specific knowledge about the environment it operates and as a consequence all initial probabilities are considered to be equal. At each instant n, an action a_i $1 \leq i \leq M$ is selected with probability $p_i(n)$. The action chosen by the automaton responds with a stohastic reaction $\beta_i(n)$, which is used to update the probability vector P. Upon completion of this update, the LA selects the next action based on the updated probability vector $p_{(n+1)}$. This means that the probabilities of some actions are increased or decreased according to the feedback received from the environment.

4.2 Adaptive Model Formulation using Learning Automata

Regarding the use of LA, in the context of this study, is the detection of an acceptable number of BVTs that should be switched off so that one manages to achieve important energy savings while maintaining the BBP

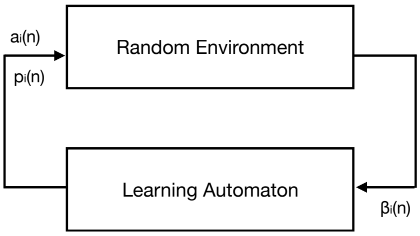


Figure 2: Operation of a Learning Automaton.

at low levels. In short, there are 2 actions that lead to the next or previous state. This way the LA, based on the corresponding probabilities, estimates where the transition will take place. Equations (5) - (12) corresponds to the probability updating scheme of the learning automaton that was described in the previous section. At each cycle n, the basic choice probability P of the selected action a is updated according to the network feedback reaction. $P_{+1}(t)$ refers to $action_{+1}$, $P_{-1}(t)$ refers to $action_{-1}$, whereas the term *state* (S) refers to the number of BVTs switched off from network nodes (i.e. S_5 corresponds to 50% of free disabled BVTs per node), as it could be seen in Figure 3. LA can then choose, based on P, whether to increase the number of BVTs to be switched off (S_{+1}) per node by $action_{+1}$, or decrease the number of BVTs to be switched off (S_{-1}) per node by $action_{-1}$. At first, the ratio of energy savings to BBP is estimated for a specific state. Afterwards, the LA checks if this ratio of the state is greater than the calculated ratio of the previous state. Should the ratio be greater or equal than the previously estimated ratio the basic choice probability of a increases according to (5), (6), (9) and (10). Otherwise, the basic choice probability of a decreases according to (7), (8), (11) and (12). L is a parameter that governs the speed of the automaton convergence. Two L values are used in this study, $L_1 = 0.01$ and $L_2 = 0.05$.

For example, it is assumed that at a certain cycle n, the LA is found at state 3 (S_3), the corresponding actions are $action_{-1}$ with $P_{-1} = 0.45$, $action_{+1}$ with $P_{+1} = 0.55$ and the ratio of energy savings to BBP is r. At cycle $n+1$, the LA chooses the action with the greater probability, P_{+1} ($action_{+1}$) and the new state is 4. Then the ratio r' for state 4 is estimated and compared to previously estimated ratio r. Should the ratio r' be greater than r, the LA receives a rewarding response and as a consequence updates the probability scheme using (5) and (6). Finally, the LA is now at state 4 and the probabilities for $action_{-1}$ and $action_{+1}$ are $P_{-1} = 0.4455$ and $P_{+1} = 0.5545$ respectively. This procedure is repeated until the LA converges to a certain state.

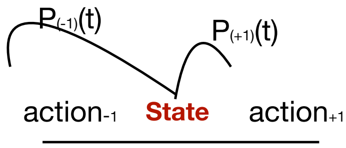


Figure 3: LESA learning mechanism.

$$P_{(+1)u}(t+1) = P_{(+1)}(t) + L_1 \times (1 - P_{(+1)}(t)) \quad (5)$$

$$P_{(-1)u}(t+1) = 1 - P_{(+1)}(t) \quad (6)$$

$$P_{(+1)d}(t+1) = P_{(+1)}(t) - L_2 \times P_{(+1)}(t) \quad (7)$$

$$P_{(-1)d}(t+1) = 1 - P_{(+1)}(t) \quad (8)$$

$$P_{(-1)u}(t+1) = P_{(-1)}(t) + L_1 \times (1 - P_{(-1)}(t)) \quad (9)$$

$$P_{(+1)u}(t+1) = 1 - P_{(-1)}(t) \quad (10)$$

$$P_{(-1)d}(t+1) = P_{(-1)}(t) - L_2 \times P_{(-1)}(t) \quad (11)$$

$$P_{(+1)d}(t+1) = 1 - P_{(-1)}(t) \quad (12)$$

4.3 Algorithm Description

The main idea of the proposed algorithm, namely LESA, is the design of an energy efficient scheme which manages to reduce the total energy consumption during network's operation, by adaptively switching off a number of BVTs in low-use scenarios without affecting the BBP. LESA algorithm consists of two separate periods. The first period involves the observation phase of the algorithm, during which calculations are made regarding the utilization of the BVTs. The second period refers to the use of LA for estimating the relation between the energy savings achieved and BBP under a different number of excluded BVTs (learning phase). Finally, the value that was indicated by the LA, constitutes the most preferred one between the energy savings achieved and BBP. That is, the number of BVTs to be switched off in order for the BBP not to be affected significantly.

During the observation period, the algorithm starts routing the traffic demands which arrive dynamically in the network. LESA calculates the shortest paths between the node pairs, using the k-shortest path method, and routes the demands according to the First Fit algorithm, while ensuring the continuity and contiguity constraint. During this phase, the existing BVTs on the physical topology, as well as the BBP are monitored for a fixed number of arrivals. Transmitters' and receivers' utilization percentages for each node in the physical topology have been calculated. Afterwards, the mean BVT utilization per node is estimated. In the final step of this period, the power consumption, using (1), (2) and (3), as well as the BBP of the initial physical topology are estimated. In addition, the algorithm outputs the number of free BVTs and the total number of BVTs per node after a certain percentage of the free BVTs have been removed. Observation's phase output is used as an input to phase two of the algorithm, the decision making with Learning Automaton phase (learning phase).

Algorithm 1 shows the pseudocode of the proposed algorithm LESA during the learning phase with a learning automata mechanism. $Tran'[i][x]$, is an array which constitutes the number of BVTs per node, where x indicates the node on the physical topology, when *i%* of the free BVTs have been removed, i.e. $i = 0\%$, 10%, 20%,.., 100%. This array corresponds to the states that the learning automaton can be found. In detail, S_2 corresponds to $i = 20\%$, while S_8 corresponds to $i = 80\%$. LA may chose to either increase the number of removed BVTs, $action_{(+1)}$, from the physical topology with $P_{(+1)}$, or decrease the number of removed BVTs, $action_{(-1)}$, from the physical topology with $P_{(-1)}$. Firstly, the algorithm chooses randomly a state *sr* and calculates BBP' for this state, as well as the energy gains (ES') of this state in comparison to PC_{total} given from phase 1. Then the algorithm retrieves the action with the highest probability from $ActionVector$ (lines 10 and 21), $action_{(+1)}$ or $action_{(-1)}$ which corresponds to S_{sr+1} or S_{sr-1} respectively, runs the simulation for a fixed number of arrivals and estimates the new BBP'' for the current state, as well as the energy gains (ES'') of this state in comparison to PC_{total} given from phase 1. Should the ratio $\frac{ES''}{BBP''}$ be greater or equal to $\frac{ES'}{BBP'}$, the learning automaton updates the updating probability scheme according to (5), (6), (9) and (10). Equations (5) and (6) are applied when the LA rewards the increment of the switched off BVTs, while (9) and (10) when the LA rewards the decrement of the switched off BVTs. Otherwise, the LA updates the updating probability scheme using (7), (8), (11) and (12). By the end of this period, the algorithm ends up (convergence of LA) with the estimated value of percentage of switched off BVTs (S).

Algorithm 1: LESA, Learning Phase.

Input:
$G(N,L)$: Physical Topology
N: Set of nodes in the network
L: Set of links in the network
PC_{total}: Total PC from Phase 1
Total BBP from Phase 1
$Tran'[i][x]$: Number of BVTs per node $x \in N$ according to i

1: $i \leftarrow$ *removedtransponders 0%, 10%, .. , 100%*
2: $S \leftarrow Tran'[i]$
3: $ActionVector \leftarrow [S, action_{(-1)}, action_{(+1)}]$
4: $action_{(-1)} \leftarrow P_{(-1)}$
5: $action_{(+1)} \leftarrow P_{(+1)}$
6: *Choose state (S) sr randomly*
7: *Calculate* ES' *compared to initial* PC_{total} *for* S_{sr}
8: *Calculate new* BBP' *for* S_{sr}
9: **while** $y \leq trainingLA, y = 0$ **do**
10: **if** $ActionVector[2] \geq ActionVector[1]$ **then**
11: $sr \leftarrow sr + 1$
12: *Run Simulation for* S_{sr}
13: *Calculate new* ES'' *and* BBP''
14: **if** $\frac{ES''}{BBP''} \geq \frac{ES'}{BBP'}$ **then**
15: *Estimate* $P_{(+1)u}(t+1)$ *using (5)*
16: *Estimate* $P_{(-1)u}(t+1)$ *using (6)*
17: **else**
18: *Estimate* $P_{(+1)d}(t+1)$ *using (7)*
19: *Estimate* $P_{(-1)d}(t+1)$ *using (8)*
20: **end if**
21: **else**
22: $sr \leftarrow sr - 1$
23: *Run Simulation for* S_{sr}
24: *Calculate new* ES'' *and* BBP''
25: **if** $\frac{ES''}{BBP''} \geq \frac{ES'}{BBP'}$ **then**
26: *Estimate* $P_{(-1)u}(t+1)$ *using (9)*
27: *Estimate* $P_{(+1)u}(t+1)$ *using (10)*
28: **else**
29: *Estimate* $P_{(-1)d}(t+1)$ *using (11)*
30: *Estimate* $P_{(+1)d}(t+1)$ *using (12)*
31: **end if**
32: **end if**
33: $y \leftarrow y + 1$
34: **end while**

Output:
Convergence of LA

5 PERFORMANCE EVALUATION

A set of simulation experiments were conducted, in order to evaluate the performance of the proposed algorithm LESA. To estimate the overall power consumption of different design solutions, the metropolitan mesh network (Antoniades et al., 2004) of Figure 4, which consists of 29 nodes and 41 links was considered.

5.1 Simulation Parameters and Assumptions

An elastic optical network simulator has been implemented, using Python 3.7 on Spyder. The number of frequency slots (FS) on a link equals to 160.

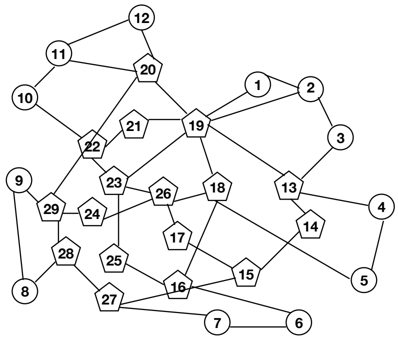


Figure 4: Mesh based Metropolitan network.

The granularity of FS is 25 GHz, while the modulation format used in every connection is assumed to be the same during the whole simulation. Also, one FS as a guard-band associated with each of the connections is considered. Connection requests follow a Poisson process with an average connection's inter arrival time ($\overline{IAT}$) equals to 1 (λ), while their holding time follows a negative exponential distribution with mean value (μ) and the offered load is determined by λ/μ (Erlangs). The latter is tuned to achieve the desired traffic load (Comellas and Junyent, 2015). The number of FSs per connection corresponds to the uniform distribution, while each new coming connection can take any value from 1 to 9 with a uniformly distributed probability (Comellas and Junyent, 2015). The source and destination nodes of a request are randomly and independently selected from the network topology. K-shortest path, with k=3, and the First Fit scheme, are used for solving the RSA problem. 400 Gbps slicable-BVTs which can launch 10 sub-carriers (a sub-carrier is associated to a FS) enabling optical grooming, and each sub-carrier can carry a 40-Gbps signal are considered in this study. The number of S-BVTs per node is assumed to be 15. Results presented below are averaged over 3×10^5 connection requests per simulation and the LA training number is assumed to be 100.

5.2 Simulation Results

In order to measure the energy-saving potential of LESA, a simple non-energy aware routing and spectrum assignment approach, namely Elastic case (Comellas and Junyent, 2015), has been implemented. Figure 5 depicts the total energy consumption versus the offered load (Erlangs) between LESA and Elastic case algorithm. Each point in the graph (concerning the LESA algorithm) corresponds to the energy consumption when using the value (S) obtained by LA mechanism after a training time (x symbol indicates the state S LA finds). The energy consumption of

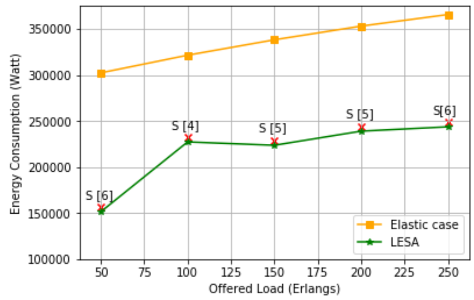


Figure 5: Energy consumption (in Watt) of LESA.

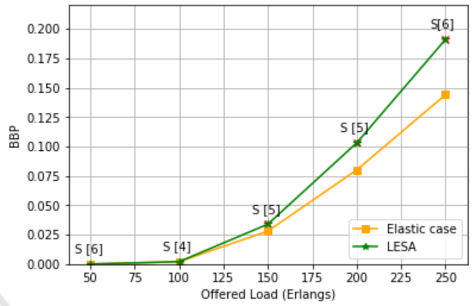
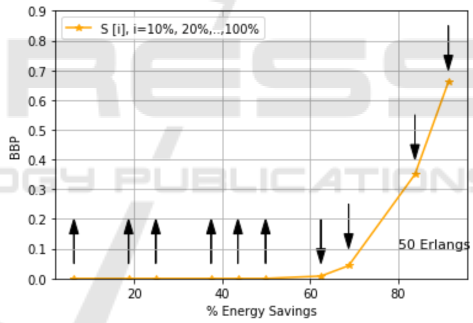
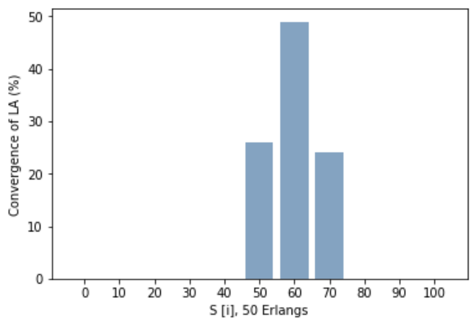


Figure 6: BBP performance of LESA.

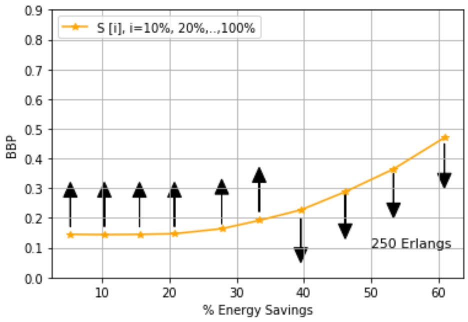


(a) Percentage of energy savings (%) and BBP for 50 Erlang under different states in LESA operation.

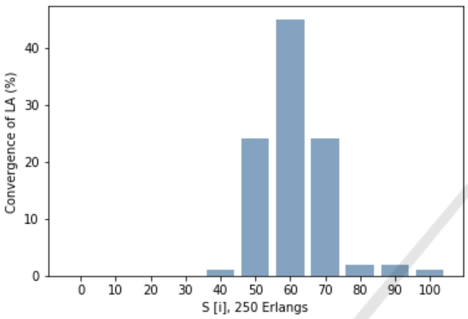


(b) Convergence of basic probabilities for different states in LESA operation.

Figure 7: LESA performance for 50 Erlang.



(a) Percentage of energy savings (%) and BBP for 250 Erlang under different states in LESA operation.



(b) Convergence of basic probabilities for different states in LESA operation.

Figure 8: LESA performance for 250 Erlang.

each compared methods rises in a common way as the offered load increases. It is worth noticing that LESA always outperforms the reference Elastic case algorithm. Corresponding results obtained in terms of power savings are summarized in Figures 7a and 8a for 50 and 250 Erlangs, respectively. These results are translated into profit by up to 50% and 33% Erlangs, respectively.

Figures 7 and 8 illustrate the obtained results of the proposed algorithm under different traffic loads. More specifically, Figures 7 and 8 show the performance evaluation of LESA for 50 and 250 Erlangs, respectively. For each traffic load, two subfigures are presented, with the first (7a and 8a) representing the percentage of energy savings under the different states of the algorithm versus the BBP, whereas the second (7b and 8b) representing the convergence of basic choice probabilities of LA towards different levels of energy-saving. The arrows shown in the line graphs (7a and 8a) correspond to the increase or decrease in the ratio $\frac{ES}{BBP}$ compared to the previous state.

An energy saving from 6% to 90% is achieved under the offered load of 50 Erlangs, while the BBP takes values from 0% to 66%, for states $S_1 = 10\%$ to $S_{10} = 100\%$, respectively (Figures 7a and 7b). In detail, for the first six states (S_1 - S_6) of the simulation the BBP remains at zero levels, while the percentage of power gain rises progressively as the number of the switched off BVTs increases, since a significant number of BVTs as well as IP router ports is reduced. For the rest of the states, the graph's curve changes significantly, as the BBP shifts at a faster rate than the energy savings. As a result, the most acceptable value of the free BVTs that should be switched off is 60% or S_6. Should 60% of free BVTs per node will be switched off from the physical topology, a power saving of about 50% is achieved, while the BBP still remains at zero levels. Observations are verified on Figure 7b which report the convergence of the LA. As it could be clearly seen, the LA chooses the preferred value of S_6 most of times with a percentage of 49%. Similar results, pertaining to 250 Erlangs can be seen in Figure 8.

Finally, BBP, in linear scale, versus the increasing offered load is depicted in Figure 6. BBP of both algorithms increases when the traffic load increases. As it could be seen, BBP remains the same as long as the offered load is up to 100 Erlangs for both LESA and Elastic case algorithm. Although, as expected in higher offered load values the Elastic case algorithm results in lower BBP, as the lightpaths have more chances to be accommodated in a network with a greater number of BVTs. However, the proposed algorithm manages to save important amounts of energy without significantly increasing the BBP.

6 CONCLUSIONS

A novel algorithm which makes use of Learning Automata (LA) in a mechanism that selectively switches off BVTs in low-load scenarios to achieve energy savings, is presented in this work. LA, based on BBP observations, aims at finding the most acceptable number of BVTs that should be switched off so that there is a noticeable increase in terms of energy gains without affecting the BBP. Simulation results verified that the proposed algorithm can achieve by up to 50% of energy savings while keeping the BBP at low levels.

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