Evolutionary Optimal Topologies for Accommodating Traffic Growth

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Abstract Modern wide-area, Wavelength Division Multiplexing-based network topologies are often meant to have a much longer lifetime than it is possible to obtain using current technologies, as the greatest cost in the network deployment process is building the infrastructure itself. Thus, it is very important to design the topology in a way that supports traffic changes resulting from population migration, introduction of new services, but network failures as well. Networks obtained this way are more likely to be easier to extend using future technological advances. In this paper, we investigate a topology design problem for future WDM-based networks, using Genetic Algorithm with Lifetime Algorithm as an evaluation function, in search for the evolutionary optimal topology. Candidate networks are being developed in the process similar to the evolution of living organisms where every generation of new networks is being assessed for its ability to survive the longest, given certain, varying traffic load. Only positively-verified network topologies are allowed to pass to another generation, simultaneously being parents to descendants obtained from them in biologically inspired processes. We use Lifetime Algorithm for determining bottlenecks and detailed lifetimes of networks, together with the new application using it to develop new topologies for the same geographical locations. We discuss the features of the networks that seem to be promoted and outline possibilities of further development of the method.

Key words Evolutionary optimal, Network Topology, Genetic Algorithm, Lifetime Algorithm, Geant Network

1. Introduction

In the modern approach to the wide area backbone network topology design, one of the outlined key points to have in mind, is that physical topology is supposed to be left unchanged for much longer than the current achievements in the optical communication would allow it to, and often empty conduits or unlit fibres are installed as a mean to provide additional network capacity when the traffic demand grows. Such an approach makes it more important to consider long-term predictions of the possible traffic shifts in the network, as the cost of building infrastructure for new fibre optic lines is significant [1]. These shifts can occur as a result of emergence of a new, enthusiastically adopted Internet service, or as a planned move of datacentres of companies offering cloud, hosting, VPS and similar services. Another concern is allocation of traffic in a way that is better load-balanced over the nodes, minimizes the effect of router failures, and maximizes predicted lifetime of the equipment before it needs to be upgraded. All of these reason have led us to the conclusion that assessing of the possibility to cope with certain shifts in traffic may not only be useful when dealing with already developed networks, to determine bottlenecks and their improvement possibility, but also in the design process of entirely new network topologies.

In this paper we investigate the possibility of using the Lifetime Algorithm [2], a method that has proven to be promising in terms of assessing the ability of a proposed network topology to survive variable load, by introducing shifts that can represent the unstable nature of the Wide Area Networks traffic schemes. We use it together with Genetic Algorithm in order to determine the characteristics of a network, which for the given dataset, technological constraints and time, proves to provide the best performance on the path of evolution. We discuss the properties of the obtained topologies and compare them, as well as the influence of different parameters we have introduced during our research to determine the optimal settings to obtain the final topology. In this paper we have focused our attention on the network nodes performance metrics, taking into account link performance in the second place. However, when considering implementation of the method in the production environment, a new, combined metrics incorporating real world geographical constraints need to be included as well.

This paper is organized as follows: in Section 2 we define assumptions of out method, together with explanation of used algorithms.

In Sections 3 and 4 we discuss sample applications of our method in two locations differing by size of the network and its application, followed by comparison of obtained results in Section 5. In Section 6 we conclude our work and present possibilities of development of the method.

2. Method used to search for the evolutionary-optimal topology

As a means to determine an optimal evolutionary developed topology we decided to use Genetic Algorithm implemented by the Genesis tool [3], in which we use a modified version of Lifetime Algorithm [2] as an evaluation function. We start by generating random topologies with fixed average starting degree, and then evaluate every one of the topologies against technological constraints. If it satisfies all of them (minimum and maximum node degree, verified connectivity between all nodes) then the topology is evaluated by sequentially loading it with each of the traffic matrices from the predefined set. Topology lifetime, defined as in [2] is calculated, by finding the node with the highest traffic and dividing the node capacity by this value to obtain multiplicity, determining how many times the traffic can grow before we need to change the node, or reroute the traffic in another way. Average lifetime for all available traffic matrices is calculated for a topology based on the average value of the node lifetime and the Genetic Algorithm orders them inside a generation according to this metric. The best obtained topologies are analysed in the second phase using stand-alone Lifetime Algorithm to calculate not only node lifetime, but also link lifetime and determine the traffic vs degree graph, which can be used to determine equipment that would be sufficient to support a given load, basing on the feasibility region as described in [4]. Moreover, we compare basic features of the current and developed topologies by utilizing CAIDA TopoStats toolkit [5], and determine features of the network that were promoted on the path of evolution.

2.1 Lifetime Algorithm

As an assessment function used in our method we have decided to use the Lifetime Algorithm [2]. Because full implementation was meant to provide an insight into how already developed topologies deal with traffic growth and shifts, which is beyond the scope of this research, we have decided to implement it selectively. With the feasibility problem, addressed there, we cope by introducing a load matrix for every evaluated topology. Then, using topology matrix and each of the traffic matrices we load links in the topology using a simple routing algorithm based on the Breadth-first search (BFS). As a next step, a node with the lowest node bandwidth/node traffic coefficient is determined, and this smallest value becomes the indicator of how many times the traffic can grow, before the node will have to be replaced. We use this value as lifetime of the topology. After initial simulations we have noticed that node lifetime tends to converge with high values of node degree, with link lifetime, which we were observing as well, being random. As a countermeasure we have decided to introduce another parameter, link importance coefficient to investigate the influence of this combined metric on the total lifetime of the topologies.

Table 1 Genetic Algorithm settings

Generations	10000
Population	100
Crossover rate	0.6
Mutation rate	0.01
Generation gap	90%
Options	R, e

2.2 Genetic Algorithm

As the implementation of the Genetic algorithm, we have used the Genesis v5.0 [3] tool. The tool implements genetic algorithm, operating on bit strings representing topologies in our case, where every bit corresponds to a single, bi-directional link which results in a total structure length of $N * (N-1)/2$ with node count N. The algorithm generates random strings with a given average starting degree parameter, to obtain randomized topologies with a predefined amount of links. All generated topologies form a first generation in the experiment which is evaluated by a selected function and used as a foundation for next generations afterwards. The scheme of the Genetic Algorithm implemented by Genesis is represented by the following pseudocode [3].

```
procedure geneticAlgorithm
  begin
    t=0;                  {generation count}
    initialize P(t);      {population in t}
    evaluate structures in P(t);
    while !terminate do
      t=t+1;
      select P(t) from P(t-1);
      recombine structures in P(t);
      evaluate structures in P(t);
    end;
  end.
```

Values of constants which we have used in Genetic Algorithm during all of the simulations are presented in Tab. 1. Generations describes the number of generations, through which the algorithm performs an evolution process with crossover and mutation rate probabilities on population count of topologies, in every following generation exchanging generation gap of topologies for the new ones. Option e assures us that the best topology will survive and R, indicate the ranking method for the selection of descendants, helps to prevent premature convergence of the algorithm.

3. Sample applications of the method

To present the sample application of the method we have chosen Japan and European Union as target geographical locations. For both of them we have defined the node count for the topologies we were going to generate, together with technological constraints which may not be violated on the path of evolution. Because of differences in location, traffic patterns and the currently deployed network topology and applications, we have used a slightly different approach in both cases, holding in mind to keep the main assumptions constant, so it would be possible to compare the final results obtained in the simulations. In the final assessment procedure we were using only node lifetime, while during evolution process, topologies were developed with the evaluation function comparing link lifetime as well, with four values of the influence of this parameter: 0%, 25%, 50% and 75%. Constants of the Lifetime Algorithm included link capacity, which has been set to 100Gbps, node capacity set to 1,28Tbps, which implies using Cisco 12000 series routers in all nodes and maximum hop count equal to 10. These were only sample values to ensure the node lifetime and link lifetime would always be positive, indicating the ability of a network to cope with already existing traffic.

4. Application to the Japan backbone network

As a first location for application of the method we have chosen Japan, setting the node count according to the number of Japanese prefectures, to simulate a country-wide optical backbone network. In the beginning we started by determining basic features of one of the already existing country-wide networks to have an insight in the constraints that should not be violated, but to better understand the needs of such a network as well. Results of our simulation are compared to these results in section 4. 3 and 4. 4.

4. 1 Data set used as a traffic reference in Japan backbone network

Because of lack of an authentic traffic matrices set available for Japanese networks, we have decided to use the method introduced in [2] to increase the dataset on which the algorithm will work, instead of just using it in the process of final topology evaluation. We generated five datasets of traffic matrices with different unexpected traffic growth (UTG) values and carried out experiments using this batch of data to determine if different values used during the generation of the new network topologies influence its performance when assessed with datasets with other values of this parameter, i.e. if any particular value used in the dataset during generation also provides us with overall better performance. The UTG parameter, as introduced in [2], for any traffic matrix $T_d(i,j)$, for every node pair $t(i,j)$ is defined as:

$$U(d(i,j))_{max} = \frac{(\sum_{i=1}^{m}\sum_{j=1}^{m} t(i,j)) - (t(i,j) + t(j,i))}{t(i,j) + t(i,j)} \quad (1)$$

Then the U, being the minimal value of UTG is chosen from the set of all obtained values for a given traffic matrix, as using a greater value would mean that traffic exceeding the total traffic in the traffic matrix has been shifted to one node pair. Subsequently, a new set of matrices is being build, in which for every node pair $t(i,j)$, we create a new traffic matrix in which traffic of the node pair in question is multiplied by $(1 + U)$, and for every other node pair by

$$r_{d(i,j)} = \frac{U(t(i,j) + t(j,i))}{(\sum_{i=1}^{m}\sum_{j=1}^{m} t(i,j)) - (t(i,j) + t(j,i))} \quad (2)$$

to preserve total traffic sum in the matrix. It is important to mention that the values of traffic, in the case of the dataset meant for Japanese topology, do not reflect reality, but are only estimations made on a basis or real percentage per node. Therefore, values presented in this research are only a sample, and give us an insight into relative node utilization.

4. 2 Algorithm settings

An additional constant required by the Genetic Algorithm and dependant on the specific network parameters, is structure lenght, which represents the amount of bi-directional links for N, the number of nodes. In case of topologies designed for a Japanese location we assumed the node count of 47, which is coherent with the prefectures count. Among variables used in this setting, were the datasets with different U parameter (20-100% of the maximum UTG) and maximum degree, which represents the maximum amount of bi-directional links that the node is allowed to utilize. Moreover, after collecting and comparing evolutionary optimal topologies, in some cases for both of the simulations for Japanese locations, we noticed that the final results obtained by competing topologies with different settings were very close. To make it clearer which topology provides a higher average node lifetime, the BFS algorithm was run in two ways, with the starting point being the node with the lowest index, followed by a run in the opposite direction to obtain two independent paths in each case, which were averaged, giving us insight into the flexibility of topologies obtained using our method.

4. 3 Numerical results obtained maximum degree of 8

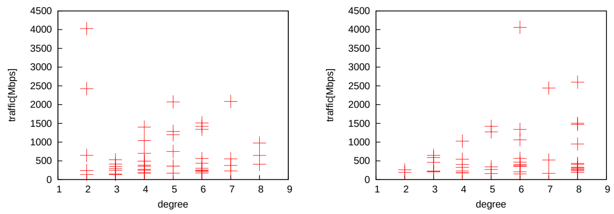
The first of the simulations was conducted with the maximum allowed node degree set to 8. We have designated two topologies as candidates for the best topology obtained in this result. The first was chosen from the topologies generated while taking into account only the node lifetime, the second one was chosen from the topologies generated using the combined metrics. Basic characteristics of topologies obtained with these settings are displayed in Tab. 2 in comparison with one of the major existing backbone topologies. With these settings we expected the average degree to reach 6, with a higher value for the topology obtained using mixed metrics, as the algorithm tends to offload the links, if link lifetime is part of the assessment, by introducing additional connections between nodes. The obtained node degree and traffic distribution among nodes is presented in Fig.1. We determined that the dataset which was used during the generation of the topology , i.e. the U parameter did not have significant meaning on the output of the algorithm. Much more important in the final results turned out to be initial average degree and link importance. Only with average degree parameter values of 3 to 5 was it possible to develop topologies with an increase in lifetime. Using an average degree of 6 and 7 it was impossible to obtain meaningful results in any experiment, as the random generator had been generating topologies with parameters violating initial

Table 2 Characteristics of topologies obtained for Japan with maximum degree of 8: Japan dataset

Metrics:	Node	Mixed	real topology
Starting avg degree	4	3	-
Links	111	133	87
Avg node degree	4.72	5.66	3.70
Assortative coefficient	-0.02	-0.22	0.09
Clustering coefficient	0.13	0.09	0.19
Average distance	2.60	2.35	3.43
Radius	3	3	4
Diameter	5	4	8

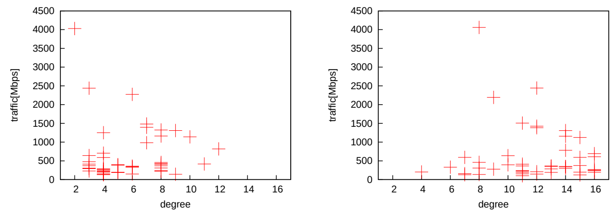
Table 3 Characteristics of topologies obtained for Japan with maximum degree of 16: Japan dataset

Metrics:	Node	Mixed	real topology
Starting avg degree	6	6	-
Links	134	278	87
Avg node degree	5.70	11.83	3.70
Assortative coefficient	-0.06	-0.09	0.09
Clustering coefficient	0.14	0.25	0.19
Average distance	2.35	1.78	3.43
Radius	3	2	4
Diameter	4	3	8



(a) node lifetime (b) mixed metrics

Fig. 1 Degree and traffic distribution of topologies with maximum degree of 8: Japan dataset



(a) node lifetime (b) mixed metrics

Fig. 2 Degree and traffic distribution of topologies with maximum degree of 16: Japan dataset

constraints in most cases. This caused the Genetic Algorithm to break off the experiment because of a lack of topologies to be assessed in the next generation.

4.4 Numerical results obtained maximum degree of 16

In the second experiment we set the maximum degree to 16 to observe the behaviour of evolution during which the algorithm had greater freedom. The starting average degree parameter of the generated topologies has varied between 5 and 7, to provide a relatively low node degree in the initial generation and avoid the situation encountered in the case of topologies generated with a maximum allowed degree of 8. This time we expected the final average degree to grow more significantly on the path of evolution, especially in case of mixed metrics, which promotes a higher edge count for the algorithm to distribute traffic uniformly. Results obtained with the maximum degree set to 16 are presented in Tab.3 together with statistics of a real world backbone network deployed in a comparable area. Traffic distribution for the nodes with different degrees in the topology is presented in Fig. 2. We noticed that the topologies obtained using only node lifetime metrics carried most traffic with more, low degree nodes while the topologies obtained using mixed metrics routed most traffic via high degree hub nodes. We verified again that the Genetic Algorithm did not promote any of the introduced U values. Moreover, we obtained meaningful results with all the available average degree values used during generation of the first population, which was caused by the relatively low values of these parameters set in the beginning of the simulation.

4.5 Discussion of numerical results for Japan dataset

In case of Japanese localisation, we found trends in topology design, that seem to be followed without difference, whether the maximum degree was set to 8 or 16. Firstly, a high average degree of nodes was not promoted, unless it was needed by the metrics assessing function. Because of this, topologies generated taking into account only node lifetime preserved a relatively low average degree. However, the output degree rose together with higher values of the average generation degree. Such behaviour was not observed in the case of topologies obtained with combined metrics, as presented in Tab. 4. The lifetimes of the topologies that achieved the highest value were compared with the full mesh topology in Fig. 3. We observed that with the U parameter value of 20% UTG, the two best of developed topologies were able to deal traffic load almost as well as the full mesh topology. However, together with growing U parameter, their lifetime has been decreasing more significantly than in case of the reference network. As for the parameters, referring strictly to the Japanese topology, which were obtained directly from Lifetime Algorithm as suggested in [2], most often the bottleneck was the Tokyo node. This was most likely because of very centralized traffic patterns in the current dataset. Moreover, the algorithm determined that the link between Osaka and Tokyo was the one limiting the link lifetime, meaning it will be the first one that will have to be upgraded. Similar results were obtained with other measured metrics as well, which included a assortativity coefficient where topologies generated using only node lifetime tended to be less assortative than the ones obtained using combined metrics, in case of both maximum degree settings. The clustering coefficient showed similar tendencies, coherent with the results of the average degree in the obtained topologies, i.e., it grew together with the average starting degree in the case of node lifetime assessment and maintained a relatively constant, higher value in case of

Table 4 Average obtained degree: Japan dataset

Metrics:	Node evaluation			Link importance 25%			Link importance 50%			Link importance 75%		
Generation degree:	3	4	5	3	4	5	3	4	5	3	4	5
Max degree 8:	5.14	5.18	5.70	5.89	5.93	5.81	5.77	5.82	5.73	5.69	5.75	5.90
Max degree 16:	5.58	6.43	7.13	12.16	12.23	12.24	12.16	12.44	12.13	12.09	12.10	12.16

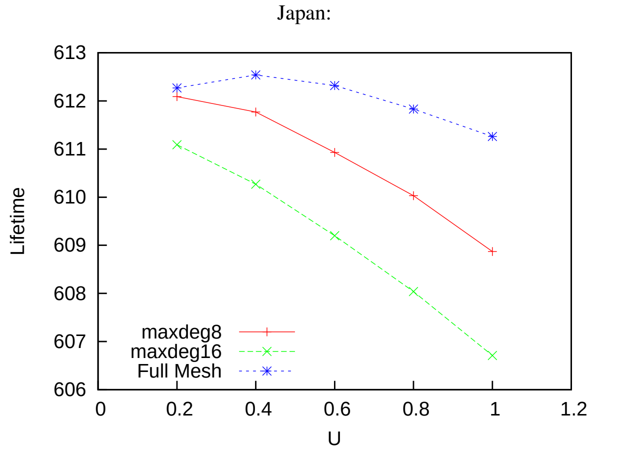
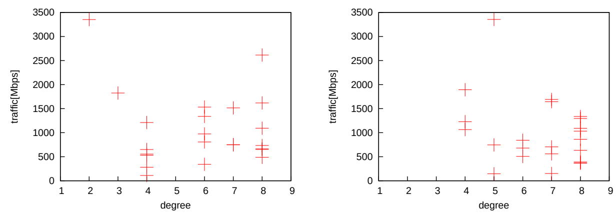


Fig. 3 Best topology lifetimes vs variation of U parameter: Japan dataset

Table 5 Characteristics of developed topologies: EU dataset

Metrics:	Node	Mixed	real topology
Starting avg degree	3	5	-
Links	68	76	37
Avg node degree	5.91	6.61	3.22
Assortative coefficient	-0.31	-0.22	-0.20
Clustering coefficient	0.21	0.21	0.05
Average distance	1.83	1.77	2.60
Radius	2	2	3
Diameter	3	3	5



(a) node lifetime (b) mixed metrics

Fig. 4 Degree and traffic distribution in topologies: EU dataset

combined metrics. average distance, radius and distance of the generated networks demonstrated similar behaviour, highly influenced by average degree, causing them to decrease proportionally to the increasing value of these characteristics.

5. Application to European Union-wide backbone network

As another location for the application of our method we selected the European Union. In this case our target was an even bigger network. However, with a lower node count representing the 23 nodes of the Geant a few years ago. In this case, we were simulating a European research backbone network, so both the traffic distribution and patterns were expected to vary greatly from the ones we had observed in the case of generating of the Japanese topology.

5.0.1 Data set used as the traffic sample

During the research we considered using the Lifetime Algorithm UTG coefficient, as in case of the topology designed for Japan. However, because the real, rich dataset was offered to the research community by the authors of [6], we decided to use it, as it could bring more convincing results. Traffic matrices gathered in this dataset constituted of a few months worth of data from the Geant network, gathered every fifteen minutes. In later research we were considering to introduce the UTG parameter for evaluation of the topologies generated in this location as well. However, because of the characteristics of the dataset we were using, it would be difficult to determine the UTG parameter that would allow us to introduce the method presented by the authors of [2].

5.1 Algorithm settings for the European Union location

In case of a European Union-wide backbone network, structure lenght was altered to reflect the 23 considered nodes. Again, the average degree of the randomly generated topologies varied between 3 and 7 to give us insight into the importance of the first generation in the simulation. In this case it was possible to obtain results from the whole range of this parameter. However, the best results were again obtained using average degree values of 3 to 5, like in the case of the Japanese simulation. Link capacity, node capacity and maximum hop count remained the same as in the case of Japanese topologies, with the main variable being the link importance coefficient.

5.2 Numerical results for the European Union-wide network

In the case of the pan-European network topology design, we were expecting different results than these obtained in the case of the Japanese location. Firstly, the algorithm was likely to prefer topologies with a higher average node degree, as more uniform traffic distribution in such a wide area backbone network was expected to cause the average degree to increase more rapidly. Moreover, we expected a higher clustering coefficient, which indicates a relatively high density of ties. The results presented in Tab. 5 confirm our predictions, as well as indicate that in the case of this topology, the assortative coefficient is significantly lower than in the case of the Japanese topology. This means there is a much higher tendency of nodes of different degree to form a link, reflecting the differences in network utilization across a pan-European network. Traffic vs node degree plots in Fig. 4 display behaviour similar to the Japanese topologies, i.e., preferring high degree hub nodes in the topology developed using mixed metrics, whilst the topology obtained only with node lifetime presents a more uniform traffic distribution.

5.3 Discussion of numerical results

Results of the topology designed for the European Union location, comparing the node lifetime and mixed metrics selection methods, were similar to those of topologies for Japan. Parameters such as link count and related average degree were not prioritized to grow when only node lifetime was assessed, and again, as in the case of the Japanese topology, had greater significance when link lifetime was considered.

6. Comparison of the two applications

In the previous sections we discussed the application of the presented method in two geographical locations. Each of these cases need to be considered separately, as they have a different scope and requirements. However, in both cases we managed to present that the method was able to determine an optimal topology for the given area and dataset representing the corresponding traffic, following the predictions we stated. This application is just a sample, as many other parameters, like link lengths, different metrics and many others were not taken into account. However, it gives an insight into the parameters that the algorithm promotes, and what useful, additional variables may be altered in order to influence the results to be more coherent with particular applications. It is important to mention that parameters such as link importance need to be selected with caution, as the difference in the values of node lifetime and link lifetime may be significant.

7. Conclusion

We managed to develop a method for searching evolutionary-optimal topologies, based on the traffic demand matrices for a given geographical area, prioritizing the biggest value of node lifetime of the evaluated topologies. The method proved to give positive results when taking into account the link lifetime as well in a form of combined metrics. By using the Genetic Algorithm, the method is very flexible, allowing to introduce additional constraints in the topology development process. It can be used for obtaining topologies for different time periods as well, by introducing alternative data sets representing the estimated bandwidth demand in the future. However, in order to apply our method to a real-world network design, other factors need to be considered, namely geographical constraints that need to be reflected. So far, the main goal of the method was to provide the highest possible node lifetime while taking into account the link lifetime in second place. However, because traffic between major nodes in distant locations is more likely to be significantly higher than in the case of big to small node traffic, the algorithm will seek to realize loading of this path in as few hops as possible. Introducing a geographically aware loading method should solve this problem, providing us with topologies better reflecting networks that are possible to realize and will be the subject of future research. Another improvement, related to the previous one, is introduction of a more advanced routing algorithm used during the loading of a path between nodes that are not directly attached to each other. It can be partially realized by the introduction of different link capacities for the links interconnecting nodes and implementing the Dijkstra algorithm, as in the OSPF routing protocol.

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