Engineering Evolutionary Algorithm to Solve Multi-objective OSPF Weight Setting Problem

Sadiq M. Sait, Mohammed H. Sqalli, and Mohammed Aijaz Mohiuddin

Computer Engineering Department
King Fahd University of Petroleum & Minerals
Dhahran-31261, Saudi Arabia
{sadiq,sqalli,aijazm}@ccse.kfupm.edu.sa

Abstract. Setting weights for Open Shortest Path First (OSPF) routing protocol is an NP-hard problem. Optimizing these weights leads to less congestion in the network while utilizing link capacities efficiently. In this paper, Simulated Evolution (SimE), a non-deterministic iterative heuristic, is engineered to solve this problem. A cost function that depends on the utilization and the extra load caused by congested links in the network is used. A *goodness* measure which is a prerequisite of SimE is designed to solve this problem. The proposed SimE algorithm is compared with Simulated Annealing. Results show that SimE explores search space intelligently due to its goodness function feature and reaches near optimal solutions very quickly.

1 Introduction

Non-deterministic iterative heuristics such as Simulated Annealing, Simulated Evolution, Genetic Algorithms etc., are stochastic algorithms that have found applications in myriad complex problems in science and engineering. They are extensively used for solving combinatorial optimization problems involving large, multi-modal search spaces, where regular constructive algorithms often fall short. One such domain that involves such non-convex problems is Routing - a fundamental engineering mechanism in computer communication networks. The optimization objective here is to determine the least expensive or best possible path between a source and destination. Routing can become increasingly complex in large networks because of the many potential intermediate nodes a packet traverses before reaching its destination [1]. To address this, the Internet is divided into smaller domains i.e., Autonomous Systems (AS). Each AS is a group of networks and routers under the authority of a single administration. An Interior Gateway Protocol (IGP) is used within an AS, while Exterior Gateway Protocols (EGP) are used to route traffic between them [2].

The TCP/IP suite has many routing protocols, one of them is the Open Shortest Path First (OSPF) Routing Protocol, used in today's Internet [1, 3]. A computationally complex component related to the OSPF routing protocol is addressed - the OSPF Weight Setting (OSPFWS) problem. Proven to be NP-hard [4], it involves setting the OSPF weights on the network links such that the network is utilized efficiently.

2 Related Work

The use of non-deterministic iterative algorithms for solving the OSPFWS problem has been previously reported. In [4], a cost function based on the utilization ranges was formulated and Tabu search [5] was used. Dynamic shortest path algorithm was applied to find multiple equidistance shortest paths between source and destination nodes [6]. Ericsson et al applied genetic algorithm to the same problem [7]. Other papers on optimizing OSPF weights [8] have either chosen weights so as to avoid multiple shortest paths from source to destination, or applied a protocol for breaking ties, thus selecting a unique shortest path for each source-destination pair. Rodrigues and Ramakrishnan [8] presented a local search procedure similar to that of Fortz and Thorup [4]. The input to the algorithm for this problem is a network topology, capacity of links and a demand matrix. The demand matrix represents the traffic between each pair of nodes present in the topology. The methodology for deriving traffic demands from operational networks is described in [9]. For other related work the reader is referred to the contributions in [10, 11].

In this paper SimE algorithm is engineered to solve the OSPFWS. An enhanced cost function proposed in our previous work is used for this problem [12].

3 Problem Statement

The OSPF Weight Setting (OSPFWS) problem can be stated as follows: Given a network topology and predicted traffic demands, find a set of OSPF weights that optimize network performance. More precisely, given a directed network $G = (N, A)$, a demand matrix D, and capacity C_a for each arc $a \in A$, it is required to find a positive integer $w_a \in [1, w_{max}]$ such that the cost function Φ is minimized; w_{max} is a user-defined upper limit. The chosen arc weights determine the shortest paths, which in turn completely determine the routing of traffic flow, the loads on the arcs, and the value of the cost function Φ. The quality of OSPF routing depends highly on the choice of weights [12]. Figure 1 depicts a topology with assigned weights in the range $[1, 20]$. A solution for this topology can be represented as $(18, 1, 7, 15, 3, 17, 5, 14, 19, 13, 18, 4, 16, 16)$. These elements (i.e., weights) are arranged in a specific order for simplicity. They are ordered in the following manner: the outgoing links from node A listed first (i.e., AB, AF), followed by the outgoing links from node B (i.e., BC, BD), and so on.

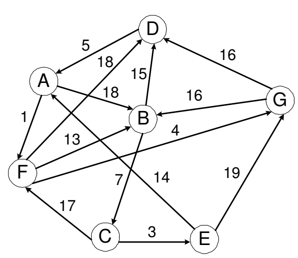

Fig. 1: Representation of a topology with assigned weights.

Mathematical Model and Cost Function

Fortz and Thorup discussed a cost function based on the utilization ranges in their paper [4], which here is denoted as FortzCF. Through experimentation it was found that this cost function does not address the optimization of the number of congested links. In our previous work, the following new cost function was proposed [12].

$$\Phi = MU + \frac{\sum_{a \in SetCA} (l_a - c_a)}{E} \quad (1)$$

This new function,denoted as NewCF, contains two terms. The first is the maximum utilization (MU) in the network. The second term represents the extra load on the network divided by the number of edges present in the network to normalize the entire cost function. The motivation behind using such a cost function is to reduce the number of congested links, if any. Consequently, the network designer will need to upgrade fewer links in the network to avoid congestion, which in turn means a less expensive upgrade.

The steps to compute the cost function Φ for a given weight setting $\{w_a\}_{a \in A}$ and a given graph $G = (N, A)$ with capacities $\{c_a\}_{a \in A}$ and demands $d_{st} \in D$ are enumerated in [12]. This procedure is also described in [13].

4 Engineering SimE for OSPFWS

SimE is a general iterative heuristic proposed by Ralph Kling [14]. It falls in the category of algorithms which emphasize the behavioral link between parents and offspring, or between reproductive populations, rather than the genetic link. This scheme combines iterative improvement and constructive perturbation and saves itself from getting trapped in local minima by following a stochastic perturbation approach. It iteratively operates a sequence of **evaluation**, **selection**, and **allocation** steps on one solution.

The selection and allocation steps constitute a compound move from the current solution to another solution of the state space. SimE proceeds as follows - It starts with a randomly or constructively generated valid initial solution. A solution is seen as a set of movable elements. Each element e_i has an associated goodness measure g_i in the interval $[0, 1]$. In the evaluation step, the goodness of each element is estimated. In the consequent selection step, a subset of elements are selected and removed from the current solution. The lower the goodness of a particular element, the higher is its selection probability. A bias parameter B is used to compensate for inaccuracies of the goodness measure. Finally, the allocation step tries to assign the selected elements to better locations. Other than these three steps, some input parameters for the algorithm are set in an earlier step known as **initialization**.

Evaluation: SimE operates on a single solution termed as the population, which consists of elements. For the OSPFWS problem, each individual or element is a weight on a link. The *Evaluation* step consists of evaluating the goodness of each individual of the current solution. The goodness measure must be a number in the range $[0, 1]$. The goodness function is a key factor of Simulated Evolution and should be carefully formulated to handle the target objective of the given problem. As two cost functions are present two corresponding goodness functions are defined as follows. For FortzCF, the goodness function is taken as:

$$g_{ij} = 1 - \Phi_{i,j}/MC \tag{2}$$

For NewCF, the goodness function proposed is:

$$g_{ij} = \begin{cases} 1 - u_{ij} & \text{for } MU \leq 1 \\ 1 - u_{ij}/MU + u_{ij}/MU^2 & \text{for } MU > 1 \end{cases} \tag{3}$$

Selection: In this stage of the algorithm, for each link i of the network, a random number $RANDOM \in [0, 1]$ is generated and compared with $g_i + B$, where B is the selection bias. If $RANDOM > g_i + B$, then weight w_i is selected for allocation. Bias B is used to control the size of the set of weights selected. For FortzCF, a bias value of -0.03 is found to be suitable through experimentation.

For NewCF, when maximum utilization is less than 1, a variable bias methodology [15] is used. The *variable bias* is a function of the quality of the current solution. When the overall solution quality is poor, a high value of bias is used, otherwise a low value is employed. The average weight goodness is a measure of how many "good" weights are present in a solution.

Allocation: During this stage of the algorithm, the selected weights are removed from the solution one at a time. For each removed weight, new weights are tried to obtain an overall better solution. For OSPFWS problem, the weight on a link lies in the range [1,20]. Different allocation schemes were tried for this problem, but we use the following scheme which provided good results both in quality and time. For all iterations, a weight window of value 4 is maintained. For example, if weight 6 is selected to change, then the values {4, 5, 7, 8} are tried. This is done to moderate the perturbation of the solution state per iteration.

5 Results and Discussion

All the test cases used here are taken from the work by Fortz and Thorup [4]. Details regarding these test cases and their characteristics can be found in [13].

Figures 2 and 3 illustrate the behavior of the proposed SimE algorithm using NewCF. These figures respectively plot the average goodness and cardinality of the selection set for test case h50N148a, i.e., 50 nodes and 148 arcs. It is observed in Figure 2 that the average goodness increases with time. In the initial stages of the search, this rate of increase is significant and tends to slow down in later iterations. This slow stage suggests that on average, the weights have been assigned their values and the point of convergence has been reached. In Figure 3, the cardinality of the selection set is shown. Here it is observed that the number of selected elements (i.e., weights) decreases as the iterations increase. This suggests

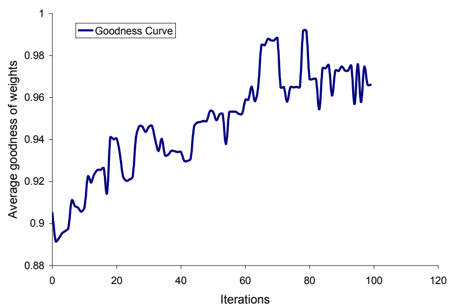

Fig. 2: Average goodness of weights for test case h50N148a NewCF.

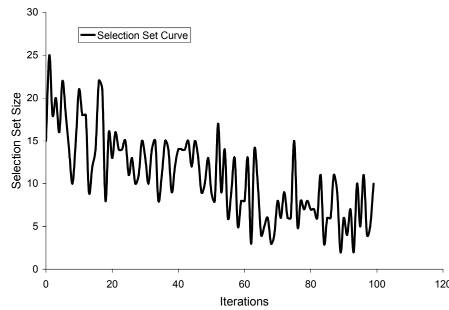

Fig. 3: Selection set size for test case h50N148a NewCF.

that the algorithm is reaching a level of convergence and therefore fewer number of weights are selected for perturbation. If the trends in Figures 2 and 3 are compared, the observation is that the convergence of the SimE algorithm towards a better solution is correlated with the average goodness of links.

Table 1 show the maximum utilization (MU) and number of congested link (NOC) values for all test cases with the highest demand values using Simulated Annealing (SA) [12] and SimE.

Table 1: MU and NOC corresponding to highest demand for all test cases (SA & SimE)

		SA				SimE			
Test case	Demand value	FortzCF		NewCF		FortzCF		NewCF	
		MU	NOC	MU	NOC	MU	NOC	MU	NOC
h100N280a	4605	1.341	8	1.341	7	1.341	23	1.341	5
h100N360a	12407	1.383	16	1.740	11	1.409	17	1.424	14
h50N148a	4928	1.271	9	1.411	9	1.532	10	1.386	9
h50N212a	3363	1.151	10	1.209	6	1.365	8	1.349	6
r100N403a	70000	1.441	95	1.826	58	1.407	81	1.402	45
r100N503a	100594	1.445	106	1.983	86	1.272	66	1.384	38
r50N228a	42281	1.218	38	1.394	22	1.316	33	1.339	20
r50N245a	53562	1.856	54	2.617	40	2.553	45	2.339	36
w100N391a	48474	1.401	1	1.424	1	1.495	1	1.284	1
w100N476a	63493	1.314	16	1.374	11	1.315	7	1.314	6
w50N169a	25411	1.252	5	1.249	3	1.252	11	1.260	5
w100N230a	39447	1.222	3	1.222	3	1.230	3	1.224	3
Average		1.358	30.083	1.566	21.417	1.457	25.417	1.421	15.667

6 Conclusion

In this paper, Simulated Evolution (SimE) is engineered to solve the the OSPFWS problem. A new proposed cost function [12] is employed which addresses the optimization of the number of congested links, and the required goodness functions are designed. The results obtained show that the engineered SimE heuristic is always able to find near-optimal solutions. Comparison with Simulated Annealing (SA) showed that the search performed by SimE is more intelligent, i.e., the solutions generated by SimE are of superior quality than that of SA and are obtained in better time.

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