Improved PSO-based Static RWA Solver Avoiding Premature Convergence

A Hassan and C Phillips

Department of Electronics Engineering, Queen Mary, University of London

Abstract: In this paper an improved Particle Swarm Optimization (PSO) scheme is proposed to solve Static Routing and Wavelength Assignment (static RWA) where the movement of the swarm particles is influenced by their personal-best position searched so far and the position of the global-best particle. Simulation results show that the proposed scheme performs better in terms of particle fitness value and average path length of the computed routes as compared to previous work. This is achieved by avoiding premature convergence of the particles in the swarm.

1. Introduction

Connection Provisioning in optical networks is carried out by setting up a *lightpath* between the end-nodes. In *All-Optical* Wavelength Division Multiplexed (WDM) networks, lightpath can traverse multiple optical link fibres; without any Optical-Electrical-Optical conversion of information carried by the lightpath at intermediate nodes. The problem of finding an appropriate route and wavelength for setting up lightpath is known as Routing and Wavelength Assignment (RWA) problem. In the static RWA case, all the connection requests are known in advance. If the intermediate nodes over the chosen route are not equipped with wavelength-conversion capability, then the same wavelength needs to be assigned to the lightpath over all the fibre links used. This property is called '*wavelength continuity constraint'*. Furthermore, two lightpaths sharing a common edge of the network need to be assigned unique wavelengths. This is called the '*wavelength clash constraint*'.

In this study we focus on two well-known and widely used network topologies, namely EON and NFSNET, shown in Figure 1 and Figure 2, respectively.

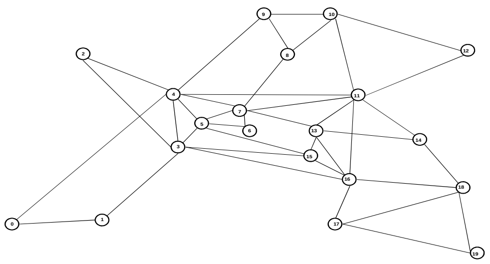

Figure1: 20 Nodes, 39 Edges EON

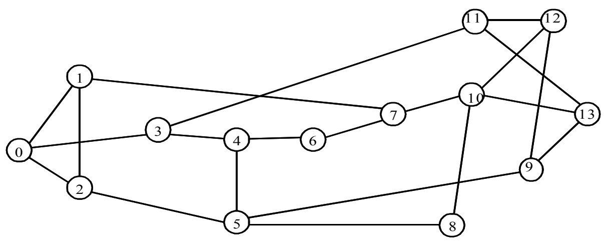

Figure 2: 14 Nodes, 21 Edges NSFNET

2. Static RWA and Related Work

Static RWA is NP (Nondeterministic - Polynomial time) hard optimization problem. The objective of static RWA is to find appropriate routes and wavelengths for all given connection requests while minimizing the network resources required. The static RWA problem can be formulated as multi-commodity problem with integer flows along each link [1]. However, when static RWA is solved by integer linear programming using a multi-commodity formulation, it results in a rapid increase in the number of equations and variables as the network complexity grows [2].

To decrease the computational demand and time required to solve NP-hard optimization problems, different heuristic based algorithms are used. PSO is an optimization algorithm inspired by swarm intelligence techniques. PSO has successfully been used to solve different NP-hard optimization problems and generally provides a better solution as compared with other swarm intelligence techniques. An overview of well-known static RWA algorithms, their functional classification, advantages and disadvantages can be found in [1, 3]. Particle swarm optimization is used to solve the static RWA in [4] with an objective function of minimizing the number of wavelengths required and average path length of the chosen routes. In [2], a novel PSO-based scheme is proposed which performs better in terms of solution quality and solves static RWA problem in significantly fewer iterations as compared to [4]. In this scheme, the movement of each particle is influenced by either the position of local-best particle in the neighbourhood or the position of global-best particle in the swarm. However, one problem with PSO-based schemes is the tendency of the swarm to converge prematurely towards a local-optimal solution. To improve the performance of PSO and to avoid premature convergence of the swarm particles, a new scheme is proposed in this paper where movement of each particle is influenced by the position of the 'global-best' particle in the swarm, or the 'personal-best' position of that particle, but not both at the same time (in a single iteration).

3. Static RWA using Particle Swarm Optimization (PSO)

PSO is a population-based algorithm inspired by social psychology metaphor that simple local interactions often lead to a complex global behaviour. A swarm is a collection of particles where each particle has a position and velocity. The position of the particle represents a candidate solution to the problem space. The velocity of the particle is used to move it to some other position i.e. some other candidate solution to the problem being studied. PSO starts by randomly initializing the particles over the problem space. A fitness function is applied to each particle in order to quantize the quality of the solution represented by that particle.

3.1. Modified PSO Equations for Solving Static RWA

In order to apply PSO for solving the RWA problem, the general PSO equations are modified so that PSO can be mapped for static RWA. In the proposed static RWA scheme, the *velocity* of movement for each particle is either influenced/governed according to position of global best particle or the personal best position of the particle searched so far (unlike [2]), but not both at any one time as shown in equation 1. The velocity is then used to determine the next position to move the particle to in the solution space where this movement is represented by equation 2.

$$V_{i+1} = \alpha * C1\,(P_{gb} - X_i) + (1 - \alpha) * C2\,(P_{pb} - X_i) \quad (1)$$

$$X_{i+1} = X_i + V_{i+1} \quad (2)$$

α is either 0 or 1. C1 & C2 are social learning parameters. 'P_{gb}' is the position of global best particle, 'P_{pb}' is particle's personal best position searched so far, 'X_i' is the current position of the particle.

3.2. Encoding Scheme for Particles

A set of pre-computed k-shortest routes is available for every possible source-destination pair in the network, where each route in the set is identified by a unique 'route-id'. During swarm initialization, for each connection request a route is chosen from the pre-computed k-shortest routes. So a particle is represented as a vector of route-ids as described in [2]. With each particle, a *common edge usage table* is attached, which will show the edge usage in the network after assignment of the routes represented in that particle.

3.3. Computation and Applying the Velocity

In each iteration, equation (1) is used to compute the new velocity of the particle. The velocity here will be a vector of route-ids that will replace the chosen routes in the current particle. The vector ($P_{gb} - X_i$) will have the route-ids of P_{gb} (Position of global-best particle) that are different from the current particle's position. The vector ($P_{pb} - X_i$) will have route-ids of P_{pb} (personal-best position of particle, searched so far) that are different in current particle's position. From ($P_{gb} - X_i$) or ($P_{pb} - X_i$), a specific number of route-ids are chosen, which will be the inserted into the velocity vector. These chosen routes (identified by route-ids) will eventually replace the routes in the current particle. C1 and C2 are constants that will determine the number of routes to be replaced in the current particle. A simple way is to choose randomly. Equation (2) is used to apply the velocity to the particle. For the static RWA problem, we need to redefine the meaning of '+' operator. The routes in the velocity vector will replace the corresponding routes in the current particle.

3.4. Fitness Function

Equation 3 is used to quantize the particles in terms of their fitness. The objective function is to minimize both average path lengths of the chosen routes and number of wavelengths required.

$$F(x) = 1 / Cost(x) \quad (3)$$

$$\mathrm{Cost}(x) = P_1 * APL + P_2 * \vartheta \quad (4)$$

APL = Average Path Length, ϑ = Number of 'directed edge disjoint route' sets. P_1&P_2 are user-defined constants. For subsequent simulations, both are assumed to be 0.5. All the routes in each of these 'directed edge disjoint route' (ϑ) set can be assigned same wavelength, as no two routes in a single set can share a common directed edge of the network [2]. However each set will be assigned a distinct wavelength. This also removes the need to have a separate 'wavelength assignment' algorithm for calculating appropriate wavelength for each route in every iteration of the particle.

3.5. Strategies to Improve Problem Space Search

In order to help the particles find a combination of routes that can move them to a position with better fitness value, three novel strategies are proposed. The first two strategies determine which particular route-ids from ($P_{gb} - X_i$) or ($P_{pb} - X_i$) vectors, will be selected to be included in velocity vector. Third one introduces a special operation for global-best particle of the swarm only. The three strategies are as follows.

(1): From current particle, select those routes for replacement first, which traverse the most congested edges of the network. The edge usage table associated with the particle can help to determine this.

(2): Instead of randomly selecting routes over the most congested edges, replace a route in the current particle with an alternate route (($P_{gb} - X_i$) or ($P_{pb} - X_i$)) only when the number of channels (congestion) of the most loaded link in the alternative route is lower than the congestion of the most loaded link in the previously assigned route.

(3): For global best, attempt 't' times to find an alternate route from pre-computed k-shortest paths, and replace it, such that congestion on the most loaded link in the alternative route is lower than the congestion of the most loaded link in the previously assigned route. (For all simulation results presented in this paper, the value of 't' is assumed to be 3)

4. Simulation Results and Analysis

A simulator is implemented in Opnet™ (http://www.opnet.com) to evaluate the performance of proposed PSO-based algorithm using personal-best and global-best search, for solving static RWA in All-Optical WDM networks shown in Figures 1 and 2. A theoretical lower bound on the 'number of wavelengths required' and lower bound on 'average path length' presented in [2] has been used here for comparison purposes. For each network, the number of connection requests will be equal to N*(N-1), where 'N' is the number nodes in the network (The same set of connection requests as in [2]). Figure 3 shows that the proposed scheme achieves near-optimal solution when compared with the theoretical bounds on the number of wavelengths required and the average path length of the chosen routes. The *'Mersenne Twister'* Generalized Feedback Shift Register (GFSR) pseudo random number generator is used for the simulations due to its properties including its long period [5].

Network	No of Particles	C_1, C_2	Iteration No. Having Best Fitness Value	Lower Bound of No. of Wavelengths required	Lower Bound of Average Path Length	APL	ϑ
NSFNET	12	0.05	4898	13	2.14	2.324176	13
EON	20	0.05	12964	18	2.36	2.786842	18

Figure 3: Comparison of the 'Number of Wavelengths Required' and 'Average Path Length' of the chosen routes, computed by the proposed scheme with respective lower bounds.

In Figure 4, 5 and 6 the performance of the proposed scheme (hereafter referred as PSO(pb)) is compared with the PSO-based static RWA solver presented in [2] (hereafter referred as PSO(lb)) in terms of fitness values (computed using equation 3), average path length of the chosen routes and the number of iterations in which swarm converges respectively. Each simulation is carried out 5 times and the average values are plotted in each case for varying number of particles in the swarm.

Figure 4 and 5 shows that the PSO (pb) scheme performs better as compared to PSO (lb) both in terms of fitness value and average path length of the chosen routes, for different number of particles in the swarm.

Performance comparison of proposed scheme PSO(pb) and PSO(lb), as described in [2]. Networks employed are shown in Figure 1 and 2.

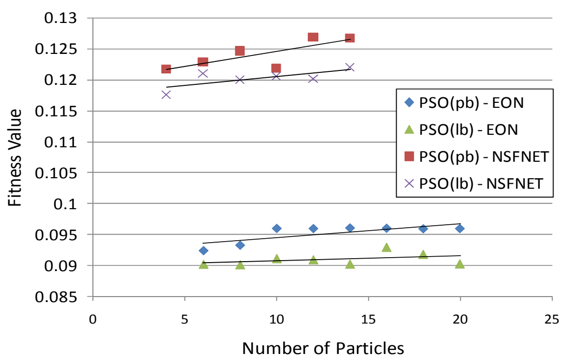

Figure 4: Fitness Value (Equation 3) versus Number of Particles

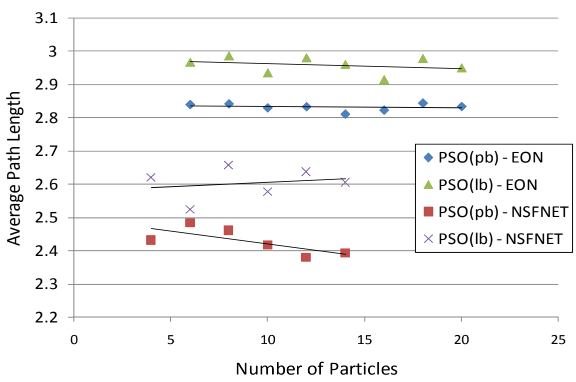

Figure 5: Average Path Length versus Number of Particles

Figure 6 shows that the PSO (pb) scheme's convergence characteristic as compared to PSO (lb). The particles in the swarm avoid premature convergence, thus giving better results (shown in Figure 4 & 5)

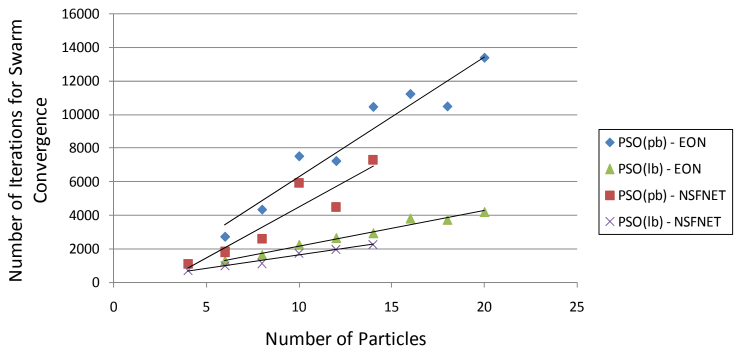

Figure 6: Performance comparison of proposed scheme in terms of swarm convergence.

5. Conclusions

In this paper PSO-based RWA solver is proposed where the particle's search of the problem space is determined by the particle's own best position (searched so far) and the position of the global best particle in the swarm. A performance comparison is made with [2], where particle's movement is influenced by the position of local best particle in the neighbourhood and global best particle in the whole swarm. Simulation results show that the proposed PSO-based solver performs better in terms of fitness value and the average path length as compared to [2] by avoiding premature convergence.

References

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