Dynamic Routing and Wavelength Assignment using Hybrid Particle Swarm Optimization for WDM Networks

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***Abstract* - This paper studies the problem of dynamic Routing and Wavelength Assignment (RWA) in Wavelength Division Multiplexed (WDM) networks with the wavelength the continuity constraint applied. A hybrid algorithm using Particle Swarm Optimization (PSO), inspired by an Ant System (AS), is used. For the routing sub-problem, particles of the swarm use the tour building approach of AS together with the exploration and exploitation approach of PSO. For the wavelength sub-problem, a first-fit algorithm is then used. Simulation results obtained for NSFNET suggest encouraging performance as compared to Ant Colony Optimization (ACO) and a Genetic Algorithm (GA) approach to solve the RWA problem.**

Key Words: Dynamic Routing and Wavelength Assignment, Particle Swarm Optimization, Ant System.

I. Introduction

WDM (Wavelength Division Multiplexing) in optical networks offers huge bandwidth capacity [1] that makes it a promising technology for next generation optical networks. In wavelength-routed WDM networks, data is routed between end-nodes in all-optical channels called 'lightpaths' [2]. If the intermediate nodes are not equipped with wavelength converters, then the same wavelength must be assigned to a lightpath along the entire route. This is called the 'wavelength continuity' constraint. For a connection request, a Routing and Wavelength Assignment (RWA) mechanism attempts to find an appropriate route for lightpath to setup and assigns a wavelength for it. The RWA approach can be categorized into two types: static and dynamic RWA [3]. In static RWA, all the lightpath requests are known in advance, and the problem is to assign routes and wavelengths in a global fashion, while minimizing the network resources [4]. In dynamic RWA, the lightpath requests arrive unexpectedly with random holding times. The objective of RWA is then to find route and assign wavelength so that the blocking probability of the connection requests is reduced. Furthermore, the RWA scheme can be divided into a 'routing sub-problem' and a 'wavelength-assignment sub-problem'. A review of different RWA algorithms can be found in [4].

Static RWA is a well known NP-Complete problem [5]. Dynamic RWA is even more challenging because the lightpath requests arrive randomly and stay in the network for random amount of time. In this case different kinds of stochastic and heuristic algorithms are used. In our paper, a hybrid Particle Swarm Optimization - Ant System (PSO-AS) scheme inspired by swarm intelligence is used to solve dynamic RWA problem under the wavelength continuity constraint. The rest of the paper is organized as follows: Section II presents our hybrid PSO-AS approach. Section III presents simulation results. Finally conclusion and future works are then discussed in Section IV.

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II. Hybrid PSO-AS System

PSO is an optimization technique, developed by Kennedy and Eberhart, inspired by *swarm intelligence*. A swarm is a collection of particles. Each particle has both a position and velocity vector. The "classical" PSO equations where the position and velocity represents physical attributes of the particles is represented by (1) and (2) [6, 7].

Calculating a Single Particle's New Velocity

$$V_{t+1} = C_1V_t + C_2\,(P_{ig} - X_t) + C_3\,(P_{\forall g} - X_t) \qquad (1)$$

"Moving" a Single Particle in a Swarm

$$X_{t+1} = X_t + V_{t+1} \qquad (2)$$

Each particle not only explores the problem space itself, it also exploits and uses the information held by the local and global best particle (i.e. the global and local best search result so far). Because of this social behaviour of 'exploration' and 'exploitation', PSO has been successfully used to solve many kinds of optimization problems. Detailed analysis of particle swarm optimization and an explanation of the above two equations can be found in [7, 8, 9]. In [10], a hybrid PSO-AS system is used to solve the well-known Travelling Salesman Problem (TSP). It demonstrates that the original PSO equations themselves do not define the specific algorithm; they just provide a communication pattern between members to affect the future actions. However some of the details of the algorithm are determined by the equation sub-definitions [10]. The effectiveness of the swarm to solve any particular problem domain depends on how the communication between the particles is exploited. It is this communication that will guide the particles to make choices that can lead them towards a better solution.

In [11, 12], heuristic algorithms are proposed to solve the problem of dynamic RWA with Ant Colony Optimization

(ACO), which is another type of swarm intelligence. Ant colonies are social, distributed systems that are highly structured. A particular focus of ant behaviour is *stigmergy*. This is a form of indirect communication, which is influenced by environmental changes that is used to co-ordinate social behaviour. The ants communicate indirectly with other ants by releasing pheromones. As an ant follows a route it releases a pheromone. The path the ant follows is influenced by the presence of the pheromone. This leads to the effect that routes chosen by a greater number of ants are more appealing than less used paths. This type of behaviour is called reinforcement learning or positive feedback.

Using ACO algorithms, a population of synthetic ants can explore a real network or its representation within a link-state database and build the source-destination route in a step-by-step process. At each node, a *pheromone* table is maintained. The decision of choosing which node will be used for a particular route is made according to the pheromone level of each possible path. The pheromone levels effectively communicate the paths that were previously followed by other ants; the path that has highest level of pheromone is normally selected.

In our proposed algorithm, the particles not only explore the network database to find new routes; they also exploit the local and global best route information (like PSO), in a step-by-step manner. A First-Fit algorithm is then used to assign wavelength to the selected route [4].

A. *Description of the Proposed PSO-AS Algorithm*

When a connection request arrives at the ingress node, a pre-determined number of particles are created. Each particle is assigned a randomly generated route. Here the “position” of the particles represents a route from source to destination node, i.e. a possible solution for dynamic RWA. So after initial random assignment of the routes, each particle will have a position. Equation 6 is used to update the fitness value of all the particles (i.e. fitness of the routes). The particle with the highest fitness value is marked as *global best*. The particle having highest fitness value in its neighbourhood is marked as *local best*. For any particle P_s, P_{s-1} and P_{s+1} will be its neighbours. Every particle will then calculate its new velocity, which will take it to the new position (i.e. a new route), given by equation 3.

$$X_{t+1} = X_t + V_{t+1} \tag{3}$$

The velocity is represented as a sequence of nodes in a particular order, and is calculated according to equations 4 and 5, in a step-by-step manner just like Ant Systems. That is, equation 5 will find just one member (next node to go) of the new velocity sequence, in a single step.

$$V_{t+1} = N_{k+1}, N_{k+2} \tag{4}$$

$\forall$ k = 1 to D-2, where N_1 = Source Node and N_D = Destination Node

$$N_\alpha = \begin{cases} P_{\forall g,t} - \omega_t & \text{if } \eta \le C_3 \\ P_{i\,g,t} - \omega_t & \text{if } \eta > C_3 \ \&\ \eta \le C_2 + C_3 \\ \text{Random Selection} & \text{if } \eta > C_2 + C_3 \ \&\ \eta \le C_1+C_2+C_3 \\ \quad \text{where\ldots}\ C_1 + C_2 + C_3 = 100\ \% & \end{cases}$$

$$\text{where\ldots}\ \alpha = k+1, k+2 \tag{5}$$

After calculating the new velocity V_{t+1}, each particle will update its current position X_t by using (3). When the particle has moved to a new position, the fitness value of the particle (i.e. fitness of the route) is updated according to (6), below.

$$F(x) = \beta^*(1/\text{hop-count}) + (1 - \beta)\,(F_w / W) \tag{6}$$

where… β = Algorithm parameter.
F_w = Number of free wavelengths available on the route.
W = Total number of wavelengths.

The meaning and function of all the variables and operators in (3), (4) and (5) is explained below.

- X_t – The particle’s current position. A position here represents a possible solution to the routing sub-problem, i.e. each position represents a route for the connection request from source to destination node.
- X_{t+1} – The particle’s new position. (moved position)
- V_{t+1} – The particle’s new velocity for the next iteration. This constitutes a sequence of step-by-step choices of node that will take the particle at position X_t, to some new position X_{t+1}. (A particle’s velocity and position contains redundant information)
- N_{k+1} and N_{k+2} – Are the chosen intermediate nodes, from source node to destination node, and will determine the particle’s new velocity.
- C_3 – A probability of selecting to use the information of the *global best*, i.e. the measure of how much a particle “trusts” the *global best* particle.
- C_2 – A probability of selecting to use the information of the *local best*, i.e. the measure of how much a particle “trusts” its *local best*.
- C_1 – A probability of selecting to use the information of particle’s own exploration, done by random search, i.e. the measure of how much a particle “trusts” its own exploration.
- “_” – Operator gives the next node in the route of first operand, from the current node. The current node at any step will be the last node of the second operand.
- $P_{i\ g,\ t}$ – Position of the local best particle, i.e. “$P_{i\ g,\ t}$” represents the local best route, searched so far.
- $P_{\forall\ g,\ t}$ – Position of the particle’s global best particle searched so far.
- ω_t – Partial route from source to destination node. When destination node will be reached, route building will be

complete; this will become the new velocity of the particle.

- $P_{i\,g,\,t} - \omega_t$ – This will give the next node in $P_{i\,g,\,t}$, from the last node in ω_t.
- $P_{\forall\,g,\,t} - \omega_t$ – This will give the next node in $P_{\forall\,g,\,t}$, from the last node in ω_t.

B. *Pseudo-Code of the Hybrid PSO Algorithm*

The pseudo-code of the main steps in our algorithm to find a suitable route for the connection request can be summarized as follows:

[Start of Hybrid PSO]

- Initialize all the particles with randomly generated routes from source to destination nodes.
- Update the fitness value of each particle, along with local and global best values (global/local best searched so far).

[Start of Iteration]

For each particle do:

Start with the source node; repeat until destination node is found. Mark the node selected as current node.

Generate a random number ‘η’.

If ($\eta \le C_3$)

Select the immediate node next to the current node in $P_{\forall\,g,\,t,}$ (i.e. global best route, searched so far), if that’s not repeated in the partial path ω_t. If no information in the global route can be used, use local best route information.

If ($\eta > C_3$ & $\eta \le C_2 + C_3$)

Select the immediate node next to the current node in $P_{i\,g,\,t}$, (i.e. Local best route, searched so far), if that’s not repeated in the partial path ω_t. If no information in the local route can be used, use random search.

If ($\eta > C_2 + C_3$ & $\eta \le C_1 + C_2 + C_3$)

Randomly select any node from the current node, such that selected node is not repeated in ω_t (partial route).

Repeat until destination node is found.

Update the fitness value of each particle using (6) (i.e. the fitness value of the route they represent), along with local and global best values.

[End of iteration]

Repeat [Iteration], till there is no improvement in the global best value for a pre-defined number of iterations.

[End of hybrid PSO]

C. *An Example*

Let’s look at an example to illustrate, how this hybrid PSO system works. At any time, ‘t’, a connection request arrives, to setup a connection from node 1 to node 11, for NSFNET shown in the Fig 1. Assume there is no free wavelength available between the node ‘1’ and node ‘0’. The particles will be initialized with randomly generated routes, such that no route includes the edge between node ‘1’ and node ‘0’. In this example, one full iteration is demonstrated showing how a particle at position X_t, will find new route by randomly ‘exploring’ the search space and by ‘exploiting’ the route information of local and global best particle.

Source node = 1, Destination node = 11

$X_t = \{1, 2, 5, 8, 10, 12, 9, 13, 11\}$

$P_{i\,g,\,t} = \{1, 2, 5, 9, 12, 11\}$

$P_{\forall\,g,\,t} = \{1, 7, 10, 13, 11\}$

$C_1 = 10\%$, $C_2 = 10\%$, $C_3 = 80\%$, Random numbers generated = {89, 12, 97, 54, 77, 30}, ω_t = {empty}

Step 1:
Starting with the source node ‘1’, η = 89. Since $\eta > C_3$ & $\eta \le C_2 + C_3$, the local best information is used. Node ‘2’ is selected, as it follows the current node ‘1’ in $P_{i\,g,\,t}$. So, $\omega_t = \{2\}$. Now for the next step, the current node will be the last node in ω_t, i.e. Node ‘2’.

Step 2:
η = 12. Since $\eta \le C_3$, therefore the global best information will be used. But there is no node in $P_{\forall\,g,\,t}$ which follows the current node ‘2’. In this case we can’t use the global information, for this step. The particle will then try to use the local best information. In $P_{i\,g,\,t}$, node ‘5’ follows the current node ‘2’. So, $\omega_t = \{2, 5\}$, and the current node will now be node ‘5’.

Step 3:
η = 97. Since if $\eta > C_2 + C_3$ & $\eta \le C_1 + C_2 + C_3$, therefore the particle will explore the options randomly. At this step, the node options are 8 and 9 (Node ‘2’ is already in ω_t). Let’s say, node ‘8’ is selected randomly. So, $\omega_t = \{2, 5, 8\}$. The current node will be Node ‘8’.

Step 4:
η = 54. Since $\eta \le C_3$, global information will be used. But there is no node in $P_{\forall\,g,\,t}$ which follows the current node ’8’. So the particle will try to use the local best information. Again there is no node in $P_{i\,g,\,t}$, which follows the current node ‘8’. So the particle will choose randomly. Let’s say node ‘10’ is chosen. So, $\omega_t = \{2, 5, 8, 10\}$, and the current node will now be node ‘10’.

Step 5:
η = 77. Since $\eta \le C_3$, global information will be used. Node ‘13’ is selected, as it follows the current node in $P_{\forall\,g,\,t}$. So, $\omega_t = \{2, 5, 8, 10, 13\}$ and the current node will now be ‘13’.

Step 6:
η = 30. Since $\eta \le C_3$, global information will be used. Node '11' is selected, as it follows the current node in $P_{\forall g, t}$. So, ω_t = {2, 5, 8, 10, 13, 11} and the current node will now be '11'.

Since node '11' is the destination node, so the partial route ω_t will become the next velocity V_{t+1} for this particle. When this velocity will be applied to the particle at position X_t, according to (3), the particle will move to the new position X_{t+1}, given by: X_{t+1} = {1, 2, 5, 8, 10, 13, 11}.

As we can see, in the new velocity V_{t+1}, node '2' and '5' are chosen using local best information. Node '13' and '11' are chosen using global best information. And node '8' and '10' are selected by the particle's own exploration using random search. So the particles are not only randomly exploring the network but also exploiting the local and global best information (Exploration and Exploitation).

III. Simulation Results and Analysis

The proposed algorithm has been implemented using Visual C++.net, without any code optimization on Dell Optiplex GX520 (CPU 3.00 GHz, 1.99 GB of RAM) in windows environment. A centralised resource management architecture is assumed for the experiments. The primary focus is to analyse the blocking probability of the proposed algorithm as compared to other heuristic algorithms like genetic algorithm, ant colony optimization etc. 8 particles are used for each connection request. If the particles cannot find route for the connection request within 5 iterations, the connection will be blocked. When a connection is established successfully or is blocked, all the particles created for that specific connection request are destroyed. For the purpose of results comparison, the blocking probability of the hybrid PSO scheme is compared with [3] and [12] for NSFNET comprising 14 nodes, 21 edges, and 8 wavelengths per edge as shown in Figure 1. For wavelength assignment, a first-fit algorithm is used [4].

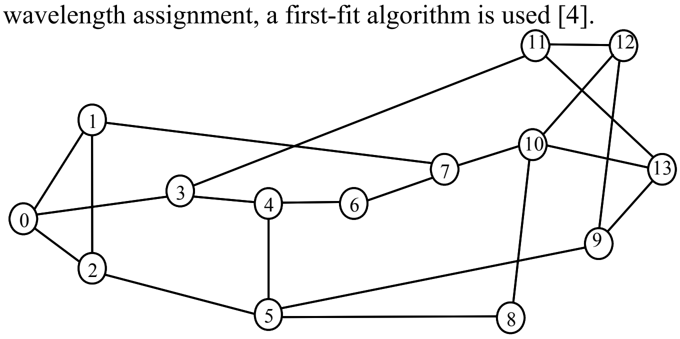

Figure 1: 14-Node, 21 Edges NSFNET

For the experiments, a dynamic traffic model is used in which connection requests arrive at the network according to Poisson process with an arrival rate of 'λ' (connections/unit time). The mean connection holding time is 'μ' (time units). The connection requests are distributed randomly on all the network nodes. If there are 'N' sessions over the network, then the total network load is measured as N * λ * μ (Erlangs).

As compared to [3] and [12], the proposed algorithm shows significant improvement in the blocking probability. Examining Figure 2 we see that at a workload of 100 Erlangs, the proposed algorithm has a blocking probability of 0.0093. However, in the case of [3], the blocking probability is 0.010 approximately for a workload of less than 70 Erlangs, and [12] shows the blocking probability of 0.04 (approx.) for a work load of 100 Erlangs (approx.).

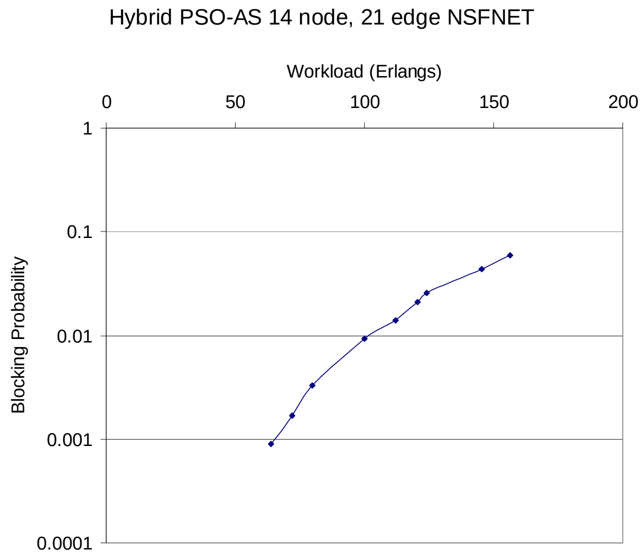

Figure 2: Blocking Probability versus Workload
14-node, 21-edge, single fibre, 8 wavelengths NSFNET.
β = 0.9, C_1 = 10%, C_2 = 10%, C_3 = 80%

In the Genetic Algorithm (GA) – survival of the fittest approach, a selection operator is used to eliminate the members from the population, having poor fitness value [13]. Therefore, the fitness function in GA needs to be designed with extreme care, because it is this function, which will guide the selection operator to include or exclude a member in the next generation. However in the proposed algorithm (as in original PSO), all the members of the population (i.e. particles of the swarm) exist throughout the duration of the problem search and evolve towards better solution. This is because there can always be a possibility, that a member having poor fitness value in the initial iterations, evolves to be the best member of the population. The proposed algorithm uses the step-by-step route building approach of ACO to build a possible route from source to destination node. However, unlike ACO, no pheromone table needs to be kept at each node.

IV. Conclusion and Future Work

In this paper, a hybrid particle swarm optimization algorithm is proposed to solve dynamic routing and wavelength assignment problem. Simulation results show that when compared to genetic algorithm in [3] and ant colony optimization in [12], the proposed algorithm shows significant improvement in terms of blocking probability. Future work will examine the effect of number of particles on connection setup time and convergence time. Extensive comparison of different network performance measures against other heuristic and stochastic algorithms will be carried out for different standard and randomly generated networks. Also we intend to extend this algorithm so that it can be applied to networks with partial wavelength conversion capability.

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