# PARTICLE SWARM OPTIMIZATION FOR ROUTING AND WAVELENGTH ASSIGNMENT IN NEXT GENERATION WDM NETWORKS

**By**

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# DECLARATION

I hereby declare that the work presented in this thesis is solely my work and that to the best of my knowledge the work is original except where indicated by reference to respective authors.

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# ABSTRACT

All-optical Wave Division Multiplexed (WDM) networking is a promising technology for long-haul backbone and large metropolitan optical networks in order to meet the non-diminishing bandwidth demands of future applications and services. Examples could include archival and recovery of data to/from Storage Area Networks (i.e. for banks), High bandwidth medical imaging (for remote operations), High Definition (HD) digital broadcast and streaming over the Internet, distributed orchestrated computing, and peak-demand short-term connectivity for Access Network providers and wireless network operators for backhaul surges. One desirable feature is fast and automatic provisioning. Connection (lightpath) provisioning in optically switched networks requires both route computation and a single wavelength to be assigned for the lightpath. This is called as Routing and Wavelength Assignment (RWA). RWA can be classified as static RWA and dynamic RWA. Static RWA is an NP-hard (non-polynomial time hard) optimisation task. Dynamic RWA is even more challenging as connection requests arrive dynamically, on-the-fly and have random connection holding times. Traditionally, global-optimum mathematical search schemes like integer linear programming and graph colouring are used to find an optimal solution for NP-hard problems. However such schemes become unusable for connection provisioning in a dynamic environment, due to the computational complexity and time required to undertake the search. To perform dynamic provisioning, different heuristic and stochastic techniques are used.

Particle Swarm Optimisation (PSO) is a population-based global optimisation scheme that belongs to the class of evolutionary search algorithms and has successfully been used to solve many NP-hard optimisation problems in both static and dynamic environments. In this thesis, a novel PSO based scheme is proposed to solve the static RWA case, which can achieve optimal/near-optimal solution. In order to reduce the risk of premature convergence of the swarm and to avoid selecting local optima, a search scheme is proposed to solve the static RWA, based on the position of swarm's global best particle and personal best position of each particle.

To solve dynamic RWA problem, a PSO based scheme is proposed which can provision a connection within a fraction of a second. This feature is crucial to provisioning services like bandwidth on demand connectivity. To improve the convergence speed of the swarm towards an optimal/near-optimal solution, a novel chaotic factor is introduced into the PSO algorithm, i.e. CPSO, which helps the swarm to reach a relatively good solution in fewer iterations. Experimental results for PSO/CPSO based dynamic RWA algorithms show that the proposed schemes perform better as compared to other evolutionary techniques like genetic algorithms, ant colony optimization. This is both in terms of quality of solution and computation time. The proposed schemes also show significant improvement in blocking probability performance as compared to traditional dynamic RWA schemes like SP-FF and SP-MU algorithms.

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# GLOSSARY

| | |
|---|---|
| ACO | Ant Colony Optimization |
| APL | Average Path Length |
| ASON | Automatically Switched Optical Network |
| ASTN | Automatic Switched Transport Network |
| ATM | Asynchronous transfer mode |
| CDM | Code Division Multiplexing |
| CPSO | Chaotic Particle Swarm Optimization |
| CPU | Central Processing Unit |
| CR-LDP | Constraint-based Routed Label Distribution Protocol |
| CSPF | Constraint-based SPF |
| DIR | Destination Initiated Reservation |
| DLE | Dynamic Lightpath Establishment |
| DRWA | Dynamic Routing and Wavelength Assignment |
| EA | Evolutionary algorithm |
| FF | First Fit |
| FSC | Fibre Switch Capable |
| GA | Genetic Algorithm |
| GFSR | Generalized Feedback Shift Register |
| GMPLS | Generalized Multi-Protocol Label Switching |
| HD | High Definition |
| IETF | Internet Engineering Task Force |
| ILP | Integer Linear Programming |
| IP | Internet Protocol |
| IS-IS | Intermediate System-to-Intermediate System protocol |
| ITU-T | Telecommunication Standardization Sector |
| KSP | K Shortest Path |
| LASER | Light Amplification by Simulated Emission of Radiations |
| LSC | Lambda Switch Capable |
| LSDB | Link State Database |
| LMP | Link Management Protocol |
| MAN | Metropolitan Area Network |

| | |
|---|---|
| MEMS | Micro Electro Mechanical System |
| NGON | Next Generation Optical Network |
| NMS | Network Management System |
| NS | Neighbourhood Size |
| NP | Nondeterministic Polynomial time |
| OBS | Optical Burst Switching |
| OCX | Optical Cross Connect |
| O-E-O | Optical to Electrical to Optical |
| OIF | Optical Internetworking Forum |
| OOK | On Off Keying |
| OPEX | Operational Expenditure |
| OPS | Optical Packet Switching |
| OSPF-TE | Open Shortest Path First with Traffic Engineering extensions |
| OTN | Optical Transport Network |
| PSC | Packet Switched Capable interfaces |
| PSO | Particle Swarm Optimization |
| RCL | Relative Capacity Loss |
| ROADM | Reconfigurable Optical Add Drop Multiplexer |
| RSVP-TE | Resource Reservation Protocol with Traffic Engineering |
| RWA | Routing and Wavelength Assignment |
| SDH | Synchronous Digital Hierarchy |
| SI | Swarm Intelligence |
| SLE | Static Lightpath Establishment |
| SNMP | Simple Network Management Protocol |
| SOA | Semiconductor Optical Amplifiers |
| SONET | Synchronous Optical Network |
| SPF | Shortest Path First routing |
| SP-FF | Shortest Path with First Fit |
| SP-MU | Shortest Path – Most Used |
| SRWA | Static Routing and Wavelength Assignment |
| TDM | Time Division Multiplexing |
| VoD | Video on Demand |
| WDM | Wavelength Division Multiplexing |

# CHAPTER 1 INTRODUCTION

## 1.1. Background

Optical networking technology is an attractive candidate to meet the non-diminishing bandwidth requirements of end users, emerging applications and services. Bandwidth intensive applications like distributed database applications, High Definition-Video on Demand (HD-VoD), ultra HD digital broadcasting and steaming over the internet [1], rapid data transfers used by large scale science applications like imaging, complex modelling and visualization [2], grid computing [3] etc have strained the traditional long-haul and backbone optical networks. Innovative services like bandwidth-on-demand, Optical Virtual Private Networking and so forth require optical connections to be deployed and dropped dynamically, possibly within several seconds. This surge in the bandwidth demand has led the network operators to deploy more fibres and to consider migration from existing optical technologies to better transparent optical transport networks for the reasons of capacity expansion, intelligent network management, reducing operational costs and fast service provisioning.

WDM (Wavelength Division Multiplexed) optical networks offers huge capacity as separate channels can co-exist within a single fibre. End users communicate via optical channels called 'lightpaths' between them. However, in order to route information along paths over a series of these links generally requires a process call Optical-Electrical-Optical (O-E-O) conversion inside Optical Cross Connect (OXC) devices so that the information can be interrogated and re-modulated onto a different channel for each leg of its journey. In all-optical WDM networks this process can be simplified allowing the information arriving at the OXC to remain encoded onto a particular wavelength that is simply redirected to the appropriate output, typically using Micro-Electro-Mechanical Systems (MEMS) [4]. Reconfigurable Optical Add-Drop Multiplexer (ROADM) [5] allows the network control plane to drop desired wavelengths at any network node, while optically bypassing the rest. This way only wavelengths destined for that node will be dropped and subsequently will undergo O-E conversion.

When a connection request is made to setup a new end-to-end lightpath, a Routing and Wavelength Assignment (RWA) [6] mechanism attempts to find an appropriate route and assigns a wavelength for it. RWA can be categorized into two types: static and dynamic RWA. In Static RWA (SRWA), all the lightpath requests are known in advance, and the problem is to assign routes and wavelengths in a global manner, while minimizing the network resources. In Dynamic RWA (DRWA), the lightpath requests arrive unexpectedly with random holding times. The objective of DRWA is then to find route and assign wavelength so that the blocking probability of the connection requests is reduced. SRWA is a well-known NP (Nondeterministic Polynomial-time) - Hard problem [7]. DRWA is more challenging because: (1) Lightpath requests arrive randomly and stay in the network for random amount of time. (2) Network state is changing repeatedly through a series of events. The traditional mathematical search schemes like Integer Linear Programming (ILP) and graph colouring become ineffective at solving the DRWA problem because of the computational complexity [6, 8]. Therefore, different heuristic and stochastic schemes are used to solve DRWA in a reduced amount of time.

## 1.2. Problem and Motivation

Optical networks are undergoing a major transition from static legacy SONET/SDH ring-based infrastructure to Intelligent Next Generation Optical Transport Networks, where the connections can be setup, modified and released dynamically [9]. Some of the major motivations for this transition are:

- Customer demand for more bandwidth.
- Fast provisioning of services
- Need for improved and efficient network operation
- Additional deployment of more cost effective optical networks than legacy SONET/SDH networks
- New services like bandwidth-on-demand and Optical Virtual Private Networking. These require optical connections to be deployed and dropped dynamically, possibly within several seconds or minutes.

Standardization bodies and researchers are investigating different dynamic network architectures like Automatic Switched Transport Networks (ASTN) [10], Automatic Switched Optical Networks (ASON) [11] and Generalized Multi-Protocol Label Switching (GMPLS) [12] capable of dynamic and flexible connection provisioning using an intelligent control plane. Some novel dynamic network architectures like Optical Burst Switching (OBS) and Optical Packet Switching (OPS) [4, 13] have also been investigated recently. However, these architectures require a new switching and transmission architecture and have no direct migration path from today's existing static optical networks based on point-to-point WDM links to IP-over-OBS/OPS [14].

Next Generation Optical Networks (NGONs) are envisioned to be a mix of different optical networking technologies like ASON, GMPLS based Optical Networks, OBS, and OPS networks etc. One of the desirable features of NGONs is its ability to dynamically provision network resources (lightpath establishment) for connection requests with low connection blocking probability and minimal connection set-up time in order to support services like bandwidth-on-demand. In the case of circuit switched networks like ASON, the network control plane should also be able to support conventional long-lived lightpath connections. This requires the network plane to carry out efficient connection provisioning when a set of connection requests are given. Two main problems which are addressed here are:

- Dynamic routing and wavelength assignment with improved blocking probability performance and computation times.
- Optimal/near-optimal solution for static routing and wavelength assignment problem with significantly shorter computation times as compared to traditional mathematical search schemes like ILP.

## 1.3. Aims and Objective

The overall aim of the thesis is to explore the efficiency of swarm intelligence inspired Particle Swarm Optimization (PSO) approach in solving RWA problems in WDM optical networks. The research focuses on designing efficient PSO based heuristics for the dynamic RWA problem that performs better when compared to conventional and other evolutionary heuristic algorithms in terms of blocking probability for future connection requests and computational time. This work also addresses the design of a PSO based static RWA solver that can optimally/near-optimally solve static RWA problem with significantly reduced computational times. The advantages and disadvantages of PSO based heuristic approaches are examined and compared with other heuristic schemes.

## 1.4. Organization of this Thesis

The following of the thesis is organized as follows:

**Chapter 2. Next Generation Optical Networks (NGONs)** reviews the optical networking technology and its evolution towards dynamically provisioned networks offering greater flexibility and configurability over increasingly short timescales to address the demands of large capacity and to provide support for services like bandwidth on demand. Chapter 2 then summarizes recent research and standards for NGONs and WDM technology to materialize such optical networks.

**Chapter 3. Particle Swarm Optimization and NP-hard Optimization Problems** reviews different swarm intelligence based heuristic schemes used to solve NP-hard optimization problems, specifically particle swarm optimization which is a global optimization algorithm successfully being employed to solve such problems. Later in this chapter, performance comparison between different such population based heuristic schemes is given.

**Chapter 4. Routing and Wavelength Assignment (RWA)**. In this chapter an introduction to both static and dynamic routing and wavelength assignment problems is provided. Also, different constraints and objectives involved in solving RWA problem are explained. This chapter also summarizes previous work done to solve such problems, their efficiency and advantages and disadvantages are discussed.

**Chapter 5: Routing and Wavelength Assignment using Particle Swarm Optimization (Static Traffic Case)**. A novel particle swarm optimization based algorithm PSO-lb is proposed in this chapter to solve static RWA problem, when a set of connection request is given. In PSO-lb, the movement of the particle is determined by the position of particle having best fitness value in the whole swarm and the position of the particle having best fitness value in the local neighbourhood. Three novel strategies are proposed which help guide the particles to converge towards optimal/near-optimal solution for the problem being addressed. Detailed explanation of working of the PSO-lb, analysis of different algorithmic parameters involved and comparison with other heuristic schemes is provided to analyse performance of PSO-lb algorithm.

**Chapter 6. Improving Convergence of PSO based Static RWA Solver.** This chapter introduces a novel PSO-pb algorithm proposed to solve static RWA problem. In PSO-pb, the movement of the particle is determined by the position of the particle having best fitness value in the whole swarm and the position traversed by the particle itself over the problem search space experiencing best personal best fitness value. PSO-pb improves the performance of PSO-lb algorithm by avoiding the particle being trapped in local-optimum solution. A comparative study is later provided to analyse it performance.

**Chapter 7. PSO based Dynamic Routing and Wavelength Assignment (Dynamic RWA).** In this chapter dynamic RWA problem is addressed for WDM network with wavelength continuity constraint. Based on particle swarm optimization, PSO algorithm is proposed which can effectively provision lightpath connection requests within millisecond of wall-clock execution time. A novel fitness function is proposed which significantly improves the blocking probability performance of the underlying PSO based algorithm. A comparative study PSO is given against different heuristic algorithms to evaluate its effectiveness in terms of blocking probability performance and execution time.

**Chapter 8. Chaotic PSO (CPSO) based Dynamic Routing and Wavelength Assignment.** In this chapter a random factor is introduced during updating of particle's position. This helps the particle to escape the local-optimal solution and thus significantly improves the performance of PSO based dynamic RWA solver. A comparative study is carried out to analyze the benefit of this randomness introduced in PSO algorithm under different network conditions and different objective functions (fitness functions for the swarm of particles).

In the last chapter, work is concluded by discussing advantages and disadvantages of particle swarm optimization used for connection provisioning in next generation optical networks. Finally, the future works of PSO-based approach for resource management in WDM optical networks is discussed.

## 1.5. Main Contributions

Some of the major contributions of this research are summarized as follows:

- A Novel PSO based static RWA solver (PSO-lb) is proposed for all-optical WDM networks. Two strategies are proposed for guiding particles via velocity computation and by a special diversity operator for the global-best particle. These significantly improve the performance of the swarm helping it to converge on an optimal/near-optimal solution.
- The Premature convergence of PSO based static RWA solver is alleviated by using a scheme where the movement of the particle in the swarm is influenced by the personal-best position of the particle (searched so far) and position of global-best particle. This scheme for solving the static RWA problem is called PSO-pb algorithm.
- A Novel application of PSO for solving Dynamic routing and wavelength assignment problem in wavelength continuous all-optical WDM networks.
- A Novel Chaotic Particle Swarm Optimization (CPSO) algorithm is proposed to help improve the convergence capability of the PSO based dynamic RWA solver, and thus achieve superior solutions.
- A Proposed fitness function that helps PSO and CPSO algorithms achieve better blocking probability performance. It also minimizes the need to have a dynamically controlled ‘α’ parameter, required to control the influence of different factors in fitness function of PSO and CPSO algorithms.

## 1.6. Publications

1) A. Hassan, C. Phillips **"Particle swarm optimization-based DRWA for wavelength continuous WDM optical networks using a novel fitness function"**, Artificial Intelligence Review Journal, Volume 29, Pages: 305-319, DOI: 10.1007/s10462-009-9142-5, ISSN: 0269-2821 (Print) 1573-7462 (Online), Publication Date: 28th October, 2009.

2) A. Hassan, C. Phillips, **"Chaotic Particle Swarm Optimization for Dynamic Routing and Wavelength Assignment in All-Optical WDM Networks"**, 3rd IEEE International Conference on Signal Processing and Communication Systems (ICSPCS 2009), Nabraska, September 2009.

3) Ali Hassan, C. Phillips, Z. Luo, **"Swarm Intelligence Based Dynamic Routing and Wavelength Assignment for Wavelength Constrained All-Optical Networks"**, 9th IEEE International Symposium on Communication and Information Technology (ISCIT 2009), Korea, September 2009.

4) A. Hassan, C. Phillips: **"Swarm Intelligence Inspired Routing and Wavelength Assignment for All-Optical WDM Networks"**, International Conference on Information & Communication Technologies: From Theory to Applications 7-11 April 2008, Damascus, Syria. IEEE proceedings of ICTTA'08, Session: TEL03 – Optical Communications 2, Page: 495-496.

5) A Hassan, C. Phillips: **"Improved PSO-based Static RWA Solver Avoiding Premature Convergence"**. Proceedings of London Communication Symposium 2009, London-UK

6) A. Hassan, C. Phillips, **"Dynamic Routing and Wavelength Assignment using Hybrid Particle Swarm Optimization for WDM Networks"**, EPSRC PGNET 2007, 28th-29th June 2007.

# CHAPTER 2 NEXT GENERATION WDM NETWORKS

The significant capacity (over 50 terabits per second [4]), low signal attenuation (as low as 0.2 dB/km), immunity from electromagnetic interference and low power requirement have made fibre optics a dominant technology in long haul future communication networks [15]. The use of fibre optics as a medium for transmission of information between geographically separated nodes has grown tremendously over the years [16, 17]. This chapter introduces the optical networking, evolution toward Next Generation Optical Networks (NGONs), different multiplexing technologies, all-optical networking and advantages of wavelength division multiplexed optical networks and the essential networking components.

At the transmitter, the information is converted from the electrical domain to the optical domain. These optical signals are then modulated onto the electromagnetic wave carrier (light) and are then transmitted through the fibre-optical cable. At the receiver, the optical signals are demodulated and converted back to electrical domain.

## 2.1. Evolution towards Next Generation Optical Networks (NGON)

The widespread use of the internet, non-diminishing bandwidth requirements of end users, and introduction of emerging applications and services have led the network operators to consider network architectures which can fulfil current and future bandwidth demands.

Traditional optical networks are based on standards like SONET (Synchronous Optical Network) / SDH (Synchronous Digital Hierarchy) where electronic devices like switches and routers are connected by optical fibres. SONET/SDH is one of the most important standards for point-to-point optical links and these networks have been deployed globally by a large number of network operators [18]. SONET/SDH networks require time consuming optical-to-electrical conversion, signal processing and electrical-to-optical conversion of data at intermediate switches and end nodes. In the past few years, the transmission capacity of a single wavelength (e.g: 40 Gb/s) has exceeded the theoretical limit of electronic digital processing speed (10 Gb/s) [19]. Therefore, transmission capacity of optical networks is limited by the *bottleneck of electronics speed* employed in the switches, instead of the optical transmission [19, 20]. Optical fibres offer a huge bandwidth of approximately 30THz in the low loss region of the spectrum, around 1500 nm [21]. The aim of avoiding the electronic bottleneck has led to the concept of *all-optical* networks where data remains in the optical domain from source to destination node.

One of the desirable features of next generation optical networks (NGON) is automated optical provisioning [13]. Currently, the network management system (NMS) needs to be configured manually to add each new connection. At the same time, they possess the inflexibility of manual provisioning of resources or through slow and complex network management systems [22]. Provisioning of network resources for a leased bandwidth connection can take weeks or even months when multiple network operators are involved. Once set-up, these leased connections remain in place for months and years irrespective of the fact whether or not they are being utilized to their full capacity. Such time consuming provisioning of optical connections may be acceptable (though not desirable) for long haul connections. However, when it comes to a large metropolitan area network (MAN), this turnaround time of connection provisioning is not acceptable. In this case, dynamic automated provisioning becomes vital.

Some of the drawbacks of having manual resource provisioning are [22]:

- Error-prone resource provisioning
- Long provisioning time
- Inefficient resource utilization
- Complex network management
- Difficult interoperability between networks belonging to different operators
- Lack of protection in mesh-type optical networks

Dynamic provisioning of connections in optical networks can open a new opportunities for optical network providers, service providers and customers. Fast provisioning can improve the Operational Expenditure (OPEX) for network providers by removing human intervention from the network management system, connection provisioning and improving time to revenue for new services and applications. An example of dynamic connection provisioning is shown in the figure 2.1. Suppose two IP based networks are end-to-end connected via all-optical network using a distinct wavelength $\lambda_1$. The optical network has the capability of dynamic provisioning. During the operation of these IP networks, whenever they need extra bandwidth (more than what $\lambda_1$ can carry) or to relieve congestion, they can request the control plane of the optical network for another wavelength ($\lambda_2$ here) for a short period of time. The optical control plane can then take the extra resources back when the need for extra bandwidth no longer exists.

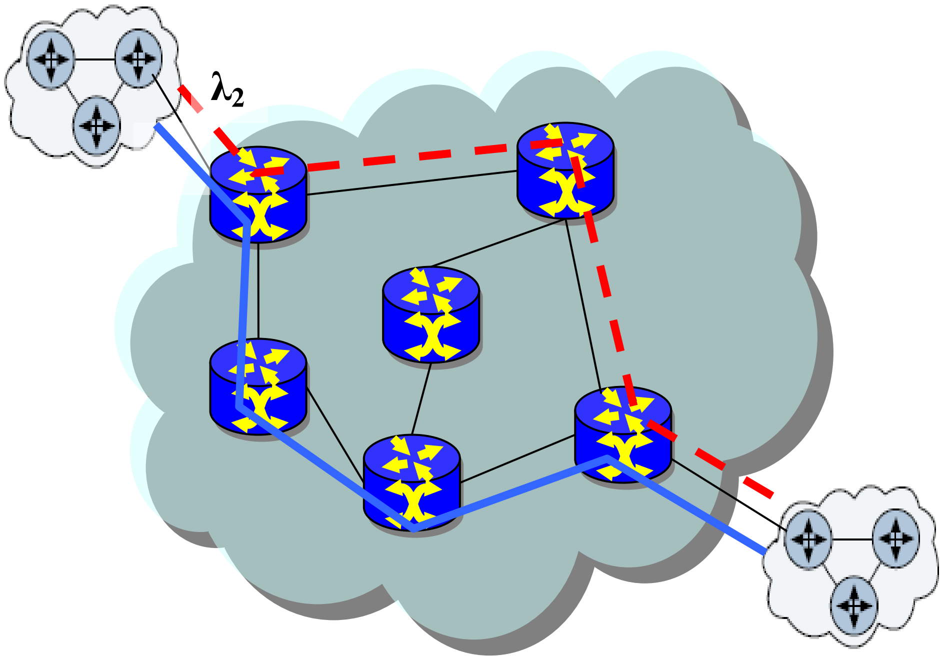


**Figure 2.1: Dynamic Connection Provisioning in Optical Networks**

For transport network carriers, fast provisioning can result in better resource utilization, allowing for efficient bandwidth management [22]. It will also help them to improve operation and management because of reduction in the manual intervention required previously. From a customer's point of view, services like bandwidth on demand can give them usage flexibility, convenience and reduction in connection provisioning time. Instead of paying for a dedicated leased line, now they have to pay only when they are using the bandwidth. For example, large financial institutions like central banks and stock exchanges etc. back up huge amounts of data to some remote backup storage facilities. One solution is to have dedicated lines that can be used to transfer bulk data overnight. Apart from backing up data overnight, these dedicated lines might not be utilized to their full capacity. However, in case of dynamic provisioning, a connection can be setup dynamically between the source of data and backup storage facility, only when there's a need. After completion of the backup, or when this connection is no longer needed, it can be released and the resources can then be used for setting up connections between other end nodes. Fast provisioning can also help to replace dedicated connections when the end parties need a high bandwidth connection to transfer time-sensitive data with minimal loss, but for brief amount of time.

Nowadays s*urvivability* of optical connections has grown into an issue of considerable importance for the wavelength division multiplexing (WDM) networks [23]. The reason is that the interruption of a high-speed optical connection (e.g.: 40GB/sec), even for few seconds means a huge loss of data. Survivability of optical connections ensures that the customers will continue to have an optical connection, even in the case of failure of an optical link or intermediate node. To provide survivability either *protection* or *restoration* schemes can be used. As shown in the figure 2.2, fast provisioning can be efficiently be used to provide survivability in an optical network removing any need to have dedicated resources provisioned for backup lightpath (protection). If any optical link or intermediate node suffers failure, a new route and wavelength is dynamically computed and connection can be provisioned rapidly.

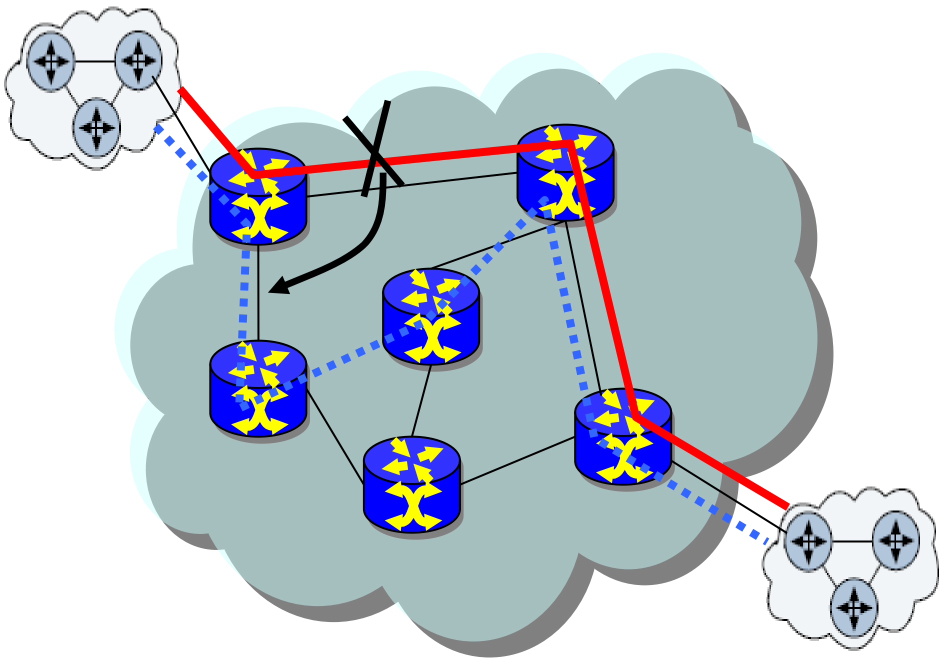

**Figure 2.2: Fault Recovery (Protection in Optical Networks)**

## 2.2. Recent Research and the Standards Context for NGON

From the last couple of years, huge effort has been made to research different architectures for Next Generation Optical Networks which can perform dynamic provisioning like Automatically Switched Optical Network (ASON), Optical Burst Switching (OBS) networks, Optical Packet Switching (OPS) networks [4, 13]. Efforts are underway in different networking standards groups like IETF, ITU-T and OIF to define protocols for fast and dynamic, end-to-end connection provisioning [9].

ITU-T's ASON architecture is considered to be a successor of the Optical Transport Network (OTN) with extended functionalities. However due to dynamic set-up and tear-down of optical channels (lightpaths), the ASON architecture has significant differences from that of OTN. ASON has separate control and transport planes and allows automatic switching of optical network connections. The three separate planes defined for ASON networks are *Optical Transport Plane, ASON Control Plane* and *Management Plane* [24] as shown in the figure 2.3. The ASON architecture also supports different kinds of optical transport services like *permanent Optical Channel Service, Semi permanent Optical Channel Service* and *Automatically Switched Optical Channel Service* [24].

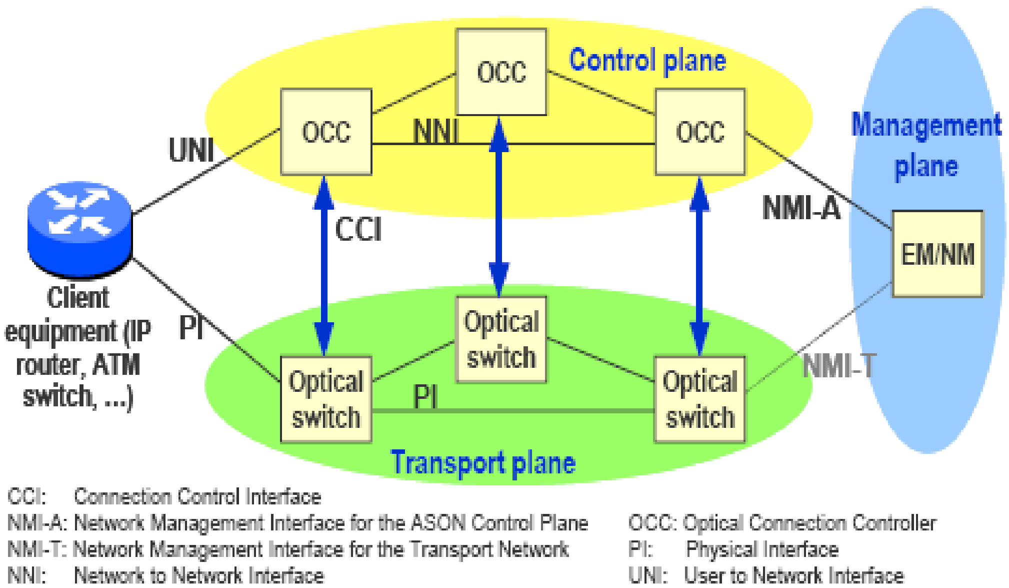


**Figure 2.3: Logical View of ASON Architecture [25]**

Generalized Multi-Protocol Label Switching (GMPLS) is a collection of protocols defined by IETF that extends IP-based network protocols. Among other capabilities, the GMPLS protocol suite also contains support for controlling network resources with different switching technologies as well as applications [26]. GMPLS enhances MPLS to support Time Division Multiplexing Capable interfaces (TDMC), Packet Switched Capable interfaces (PSC), Fibre Switch Capable interfaces (FSC) and Lambda Switch Capable interfaces (LSC) [13]. These protocols also include a new Link Management Protocol (LMP), extended signalling protocols like Constraint-based Routed Label Distribution Protocol (CR-LDP), Resource reSerVation Protocol with Traffic Engineering (RSVP-TE) and the open shortest-path-first routing protocol with traffic engineering extensions (OSPF-TE) [27]. In [28], requirements for Generalized Multi-Protocol Label Switching (GMPLS) routing for the Automatically Switched Optical Network (ASON) are explained. In [29], different routing protocols are evaluated for routing in ASON. The GMPLS suite of protocols can be used beneficially for different types of NGON architectures like ASON, OBS and OPS in order to set-up and tear-down routes dynamically.

In the OSFP routing protocol, each link is assigned an integer weight; routing simply involves a shortest path calculation with respect to the total weight of links along its route. Such a distributed control mechanism is very suitable for a dynamic environment as it reduces signalling latency. Many researchers also believe it to be applicable to next generation optical networks, since centralized ILP schemes cannot support real-time operation.

However, OSPF also poses some serious traffic engineering (TE) problems, especially when applied to circuit switched optical networks. Firstly, it calculates the shortest path with respect to link weight for a single connection at a time without taking account of other connections. The resulting placement can differ significantly from an optimal solution for the whole network. Secondly, a link in a circuit-switched network contains many more parameters than typically considered in a packet-switched IP network; in the former case some dozens of physical channels (e.g. wavelength) may exist between two nodes. However, in order to limit the burden of control traffic and OSPF database convergence time, only limited and aggregated link information can be propagated and synchronised between nodes.

This leads to inaccuracies in the OSPF database at each node, which in turn can result in sub-optimal / erroneous path calculations.

In [30], a swarm intelligence based heuristic algorithm – Ant Colony Optimization is used for routing in packet switched network. The throughput results are compared with the standard OSPF protocol as well. The results indicate that ACO performs far better than OSPF in terms of network throughput. In OSPF, there is always a possibility that some links in a network are heavily loaded, while others are almost not used. Heuristic based AntNet in [30] tries to distribute the heavy network load over several paths to keep the network in an optimal state and uses the capacity of the entire network in a more efficient way.

There are at least two solutions to cope with this type of routing inefficiency in next generation optical networks. One is to use some dynamic heuristic based algorithm for computing routes instead of using an IP-based routing protocol like OSPF. Second is to use a modified version of OSPF employing a weight optimization scheme, as in [31] where a hybrid genetic algorithm is used to solve the OSPF weight setting problem. However, in the latter case, the problem of OSPF database inaccuracies which can result in erroneous route computation, still persist.

## 2.3. Multiplexing Technologies for All-Optical Networks (WDM vs TDM vs CDM)

All-optical networks do all the processing like multiplexing, de-multiplexing, correlation, filtering and so forth, on the information transmitted across the network in the *optical-domain*. To enable sharing bandwidth offered by optical fibre among a number of clients (i.e services, applications, users), different multiplexing techniques have been proposed for all-optical networks, which are:

- Optical Time Division Multiplexing (OTDM)
- Optical Code Division Multiplexing (OCDM)
- Wavelength Division Multiplexing (WDM)

In the OTDM approach, information is transmitted across the network in the form of ultra-short optical pulses [$10^{-12}$ seconds (or pico-second (ps)) or $10^{-15}$ seconds (or femto-second (fs)) duration] at very high aggregate line rates of 100 Gb/sec and above [18], avoiding the *electronic bottleneck*. Optical processors are used to multiplex, process and de-multiplex the signals. Many lower-speed data channels are time interleaved to form a high-speed data stream as shown in the figure 2.4 below.

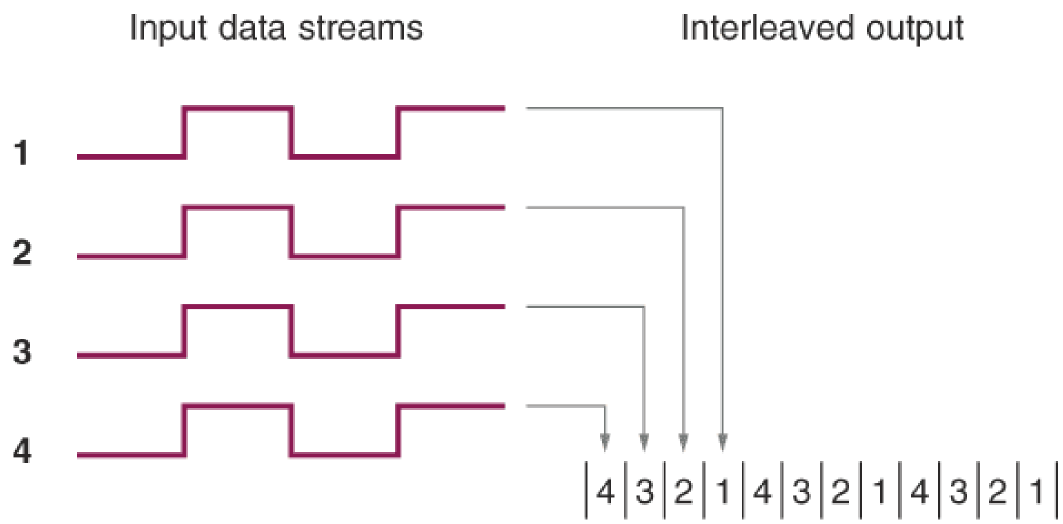


**Figure 2.4: Data stream interleaving in OTDM**

OTDM suffers from two major disadvantages: (1) Synchronization (2) Transparency. In order to avoid interference between individual lower-speed channels, transmitters should be capable of generating ultra-short pulses which are perfectly synchronized to the desired time slot, and receivers should have a perfect synchronization to time slot as well. OTDM network clients also lose transparency as they must match their traffic and protocol according to the OTDM frame structure [18].

Code Division Multiplex (CDM) is an access strategy where multiple users transmit their data concurrently over the network using a spread spectrum technique differentiated by a unique code sequence. In Optical Code Division Multiplexing (OCDM) [21], a very short pulse sequence (representing a unique code) is assigned to each channel. This unique code is used to encode/decode the low speed data. The channels are then combined and transmitted onto the high-speed optical fibre. The unique codes are selected such that the cross-correlation among other code sequences is small, and the code sequence spectrum is much larger than the bandwidth of the signal. This enables aggregation of network capacity whilst avoiding the *electronic bottleneck*. However like OTDM, OCDM requires synchronization to one chip time for correct information detection. Selecting appropriate codes for the optical domain is difficult and is limited due to orthogonality issues.

Traditionally, three low loss regions in the optical spectrum are available for use, around the 980 nm, 1310 nm and 1550 nm bands [15]. In Wavelength Division Multiplexing (WDM), the low loss region of the optical spectrum is divided into a number of channels having distinct wavelengths as shown in figure 2.5.

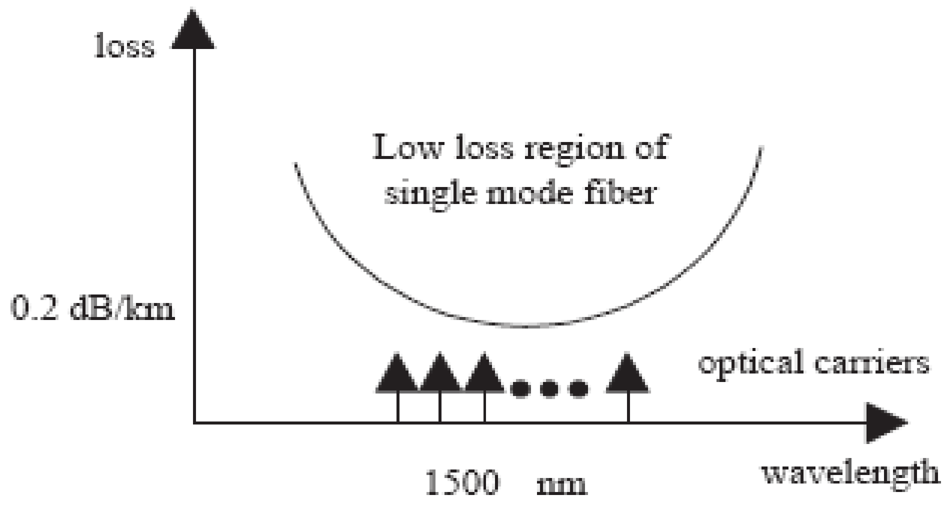


**Figure 2.5: Low Loss Region in the Spectrum for Wavelength Division Multiplexing [15]**

End nodes modulate their data onto these channels. At the transmission ingress, all the channels (having different wavelengths) are multiplexed together onto the single optical fibre. In this way WDM increases the cumulative data rate of the entire fibre. To allow users to use multiple channels simultaneously, tuneable transmitters (lasers), tuneable receivers (filters) and/or multitude of fixed transmitters/receivers are employed at end nodes. As shown in figure 2.6, each laser emits light at a distinct wavelength. All the lasers are then multiplexed together and are transmitted onto a single high bandwidth optical fibre. At the receiving node, the combined optical signal is de-multiplexed by distributing optical power at each output port. Tuneable receivers (filters) are then used to extract the desired wavelength from the optical spectrum.

All-optical WDM networks avoid the *electronic bottleneck* by optically bypassing intermediate nodes of an optical connection. Optical Add Drop Multiplexer (OADM) is used by WDM network to provide this functionality [4]. At the destination node, only a subset of wavelengths are optically dropped (i.e. demultiplexed) which are destined for that particular node, while leaving the others intact in the optical domain.

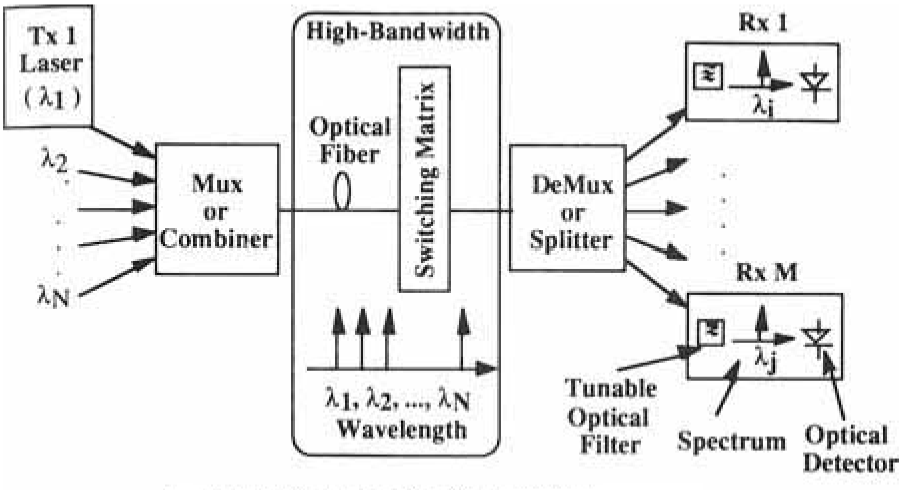


**Figure 2.6: Simple WDM system [15]**

As compared to OTDM and OCDM multiplexing schemes, WDM is favoured [21] because less hardware is required and there is no synchronization requirement (Synchronization within one time slot in the case of OTDM and synchronization within one chip time in the case of OCDM). OTDM and OCDM are relatively immature technologies as compared to WDM. WDM equipment is commercially available and is currently being used. In WDM, we have an inherent independence between the specific route to be used from the source to destination nodes and the distinct wavelength to be used for the end-to-end transmission of data. Since there is no electronic processing at intermediate nodes in all-optical WDM networks, each wavelength can be viewed as an independent channel between end nodes. Once the route and wavelength is decided, the designers of end nodes will have the flexibility to choose the bit rate, signalling and frame conventions. The transparency that WDM offers makes it possible to support different data formats and services simultaneously on the same network [21].

Commonly used WDM network architectures for long-haul and large Metropolitan Area Networks (MANs) include Broadcast and Select Networks and Wavelength Routing Networks [15, 21]. Wavelength reuse and channel splitting loss in the case of broadcast and select WDM networks limit their ability to be used for long distance core optical networks and networks having large throughputs [21]. Unlike broadcast and select networks, WDM wavelength routing networks avoid the unnecessary transmission of optical signals to nodes that do not require them. They channel the transmitted optical signal power to a specific route between source and destination nodes while avoiding broadcasting of optical signals. Wavelength routing networks also make efficient use of wavelength reuse via spatially disjoint routes across the network. In this thesis, the architectural form of WDM optical network is assumed to be a wavelength routing network as this is the most favoured architecture for long haul and large MANs. Detailed information on different architectures of WDM technology can be found in [4, 18, 21, 32 and 33].

## 2.4. WDM Networking Components

The main networking components used in WDM networks are:

### 2.4.1. Optical Transmitters

An optical transmitter essentially comprises a light source and a modulator. In optical networks, a semiconductor LASER (Light Amplification by Simulated Emission of Radiation) is usually used as the light source. The advantage of using a semiconductor laser is that it is very compact and can be fabricated in large quantities [34]. '*Tuneable lasers*' is further development within optical networks that allow the transmitter to generate different wavelengths. Table 2.1 summarizes the turning range and time for different types of transmitters [18].

**Table 2.1: Optical Transmitter Types: Tuning Range and Time [18]**

| Transmitter Type | Tuning Range | Tuning Time |
|---|---|---|
| Mechanically Tuneable | 500 nm | 1-10 ms |
| Acousto-optic | ~100 nm | ~10 µs |
| Electro-optic | 10-15 nm | 1-10 ns |
| Injection Current | ~30 nm | 15 ns |

In order to transmit the information over an optical link, the information is modulated onto an electromagnetic wave carrier. An OOK (On-Off Keying) modulation scheme is usually used due to its simplicity. Different level of signal power levels are used to represent the binary bit '1' and '0' in OOK. Two types of OOK modulation techniques are 'direct' and 'external' modulation [15].

### 2.4.2. Optical Receivers and Filters

An optical receiver typically comprises of a photo-detector to detect and decode the optical signals and convert the information from optical domain to electrical domain, an amplifier to amplify the signals in electrical domain and a signal-processing unit. Tuneable optical receivers are a further refinement of optical communication technology with their ability to sense and decode the optical signals having different wavelengths within a spectrum range. Table 2.2 summarizes some tuneable optical receivers and their associated tuning range and times [4].

**Table 2.2: Optical Receiver Types: Tuning Range and Time**

| Receiver Type | Approx Tuning Range | Tuning Time |
|---|---|---|
| Fabry-Perot | 500 nm | 1-10 ms |
| Acousto-optic | 250 nm | ~10 µs |
| Electro-optic | 16 nm | 1-10 ns |
| LC Fabry-Perot | 50 nm | 0.5 – 10 µs |

## 2.4.3. Optical Amplifiers

As optical signals propagate through the fibre-optical cable, they lose some of their power. This can result in erroneous detection of the signals at the receivers. Therefore, over distance the optical power is amplified using ‘optical amplifiers’. In a WDM optical link, optical amplification can be done at different stages as shown in the figure 2.7. Therefore, optical amplification can be used as power amplifiers, in-line amplifiers and pre-amplifiers along WDM links [34].

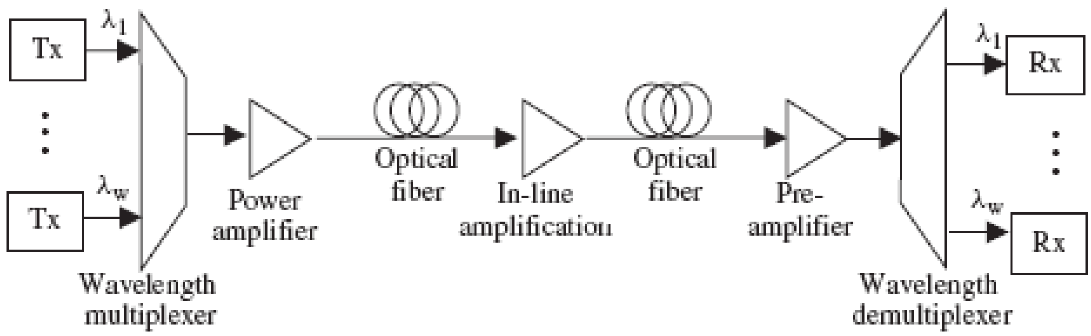


**Figure 2.7: Amplification of Optical Signal, in a point-to-point WDM link [34]**

## 2.4.4. Optical Add/Drop Multiplexer (OADM)

An Optical Add Drop Multiplexer (OADM) allows the WDM network nodes to add wavelengths to the optical signal being transmitted through a WDM link or to drop certain wavelengths from it as shown in the figure 2.8. This helps the WDM network to minimize

Optical-Electrical-Optical (O-E-O) conversion of information. At any network node, only those wavelengths are dropped which contains data destined for this particular node. The dropped signals then subsequently undergo conversion from optical domain to electrical domain. However, other wavelengths simply bypass optically and don't undergo O-E conversion.

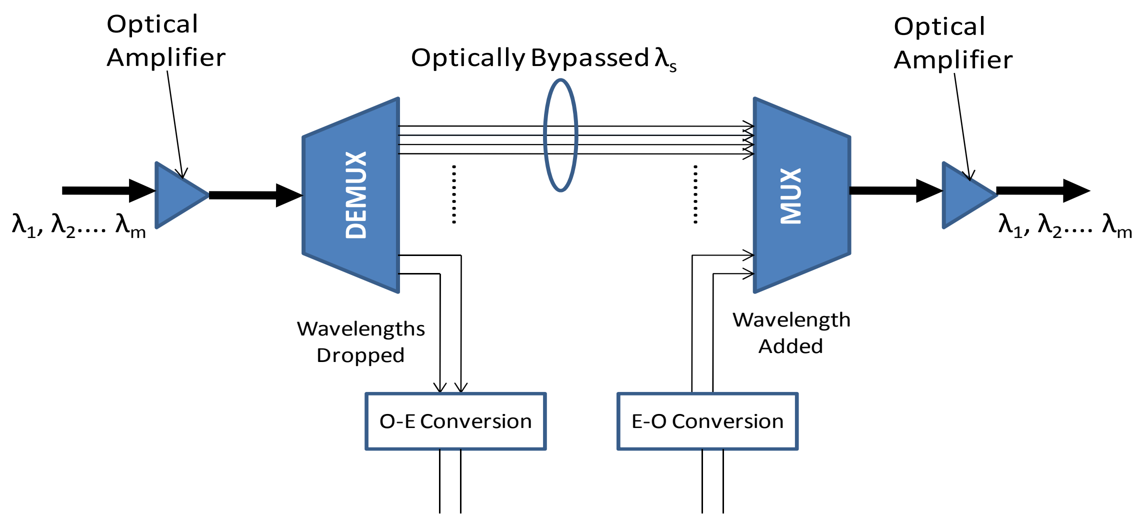


**Figure 2.8: Optical Add-Drop Multiplexer (OADM) with single WDM link carrying 'm' wavelengths**

OADMs are of two types: Fixed OADMs and Reconfigurable OADMs (ROADMs). In fixed OADMs, the wavelength that will be dropped and those which are optically bypassed are either predetermined or they can be configured manually after the installation. Reconfigurable OADM (ROADM) allows the network control plane to dropped or optically bypass any wavelength dynamically and transparently at any network node, as required by the network [4]. Detailed information about OADMs can be found in [5]

### 2.4.5. Optical Switching Elements:

An Optical Cross Connect (OCX) used in wavelength routing WDM network mainly comprises amplifiers, multiplexers/de-multiplexers, switching fabric and a CPU (Central Processing Unit)] as shown in the figure 2.9. The switching fabric of an OCX has the capability to switch an optical signal from an incoming wavelength on an input fibre, to an outgoing wavelength of some other output fibre [34]. If the switching takes place in optical domain, such optical cross connect is referred to as a transparent OCX.

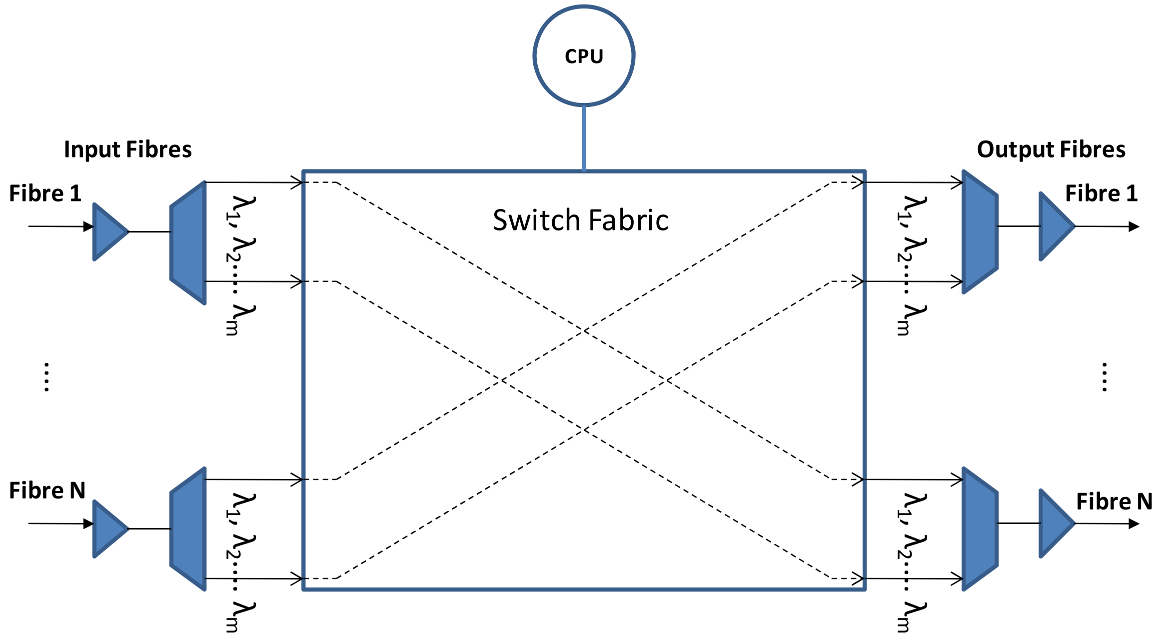


**Figure 2.9: Logical diagram of an OXC**

An Optical Cross Connect can be constructed using different technologies like digital MEMS (Micro Electronic Mechanical Systems), SOA (Semiconductor Optical Amplifiers), Mirco-Bubbles and holograms and so forth. Detailed information about these techniques can be found in [4, 34].

### 2.4.6. Wavelength Convertors

In wavelength routing WDM networks, end nodes communicate by setting up a lightpath between them. The same wavelength needs to be assigned to each lightpath over the whole route it traverses. This constraint is called the 'wavelength-continuity constraint'. However, if the network nodes are equipped with wavelength convertors, the intermediate nodes can convert an incoming wavelength onto some other outgoing wavelength. In such a network, it is not necessary, that same wavelength be assigned to the lightpath over the whole route.

# CHAPTER 3 PARTICLE SWARM OPTIMIZATION (PSO) AND NP-HARD OPTIMIZATION PROBLEMS

As human strives for perfection in different activities, this has led to the concept of optimization, which is believed to be the oldest science existing till today [35]. The primary goal of any optimization algorithm is to find a global optimal solution, while satisfying all the relevant problem constraints also known as objective functions. Global optimization search schemes can be divided into two main classes: Deterministic and Probabilistic [36].

Deterministic search schemes are those in which there always exists a single way to proceed from current execution step to the next. At any execution step, when there exists no way to proceed, the search scheme is considered to be terminated. Deterministic algorithms also yield the same output (results) for the same algorithmic inputs. The conventional *'Branch and bound'* algorithm is an example of a deterministic search scheme used to find the global optimal solution by exhaustively searching the problem domain. The main disadvantage of deterministic algorithms like *'divide and conquer'* is that they become computationally expensive even in the case of moderate sized optimization problems [8]. Their exhaustive search also makes them unusable in dynamic environments because of their inability to generate solutions quickly enough.

In probabilistic search schemes, there can exist more than one way to proceed from current execution step to the next. Random numbers can be used to decide the way forward towards the next execution step. This randomization enables the probabilistic algorithms to solve certain problems much quicker compared to deterministic algorithms [37]. However, the main disadvantage of probabilistic algorithms is the loss of reliability in the results. For example: the search carried out by a probabilistic algorithm can lead to a situation where no result at all or an incorrect result may be produced. Due to this randomization, probabilistic algorithms can yield different output (results) even for the same algorithmic inputs. Examples of probabilistic schemes are simulated annealing, hill-climbing, tabu search, genetic algorithms, swarm intelligence algorithms and many more.

In theory, a decision or an optimization problem solvable by some algorithm within a number of steps, bounded by some fixed polynomial time to the input size, belongs to the class of *‘Polynomial (P) time’* problem [38]. In other words, polynomial time decision problems are those which can be solved on a deterministic machine sequentially, in an amount of time which is polynomial to the size of the input. NP (Non-deterministic Polynomial) time problems are those decision problems for which it’s not possible to determine whether they can be solved in polynomial time or not [39, 40]. However, if somehow the solution to an NP problem is known, verification of the solution itself can be done quickly in polynomial time. NP optimization problems can be divided further into two categories: NP-complete and NP-hard problems. NP-complete problems are those which may or may-not be solved in polynomial time. However, a problem is said to be an NP-hard problem, if the algorithm used for solving it can be transformed to solve any non-deterministic polynomial time problem [7]. Such an algorithm is unlikely to be discovered for most of the NP-hard problems [41].

Another classification for optimization problems is done in terms of the environment in which they are being solved. They can generally be divided into two categories, *static* and *dynamic*. A static optimization problem is one which is defined by the initial problem definition while its environment remains unchanged throughout the search over the problem space. On the other hand, the environment of a d*ynamic optimization problem* repeatedly undergoes change caused by a series of events [42]. The dynamic nature of environment makes these NP-hard problems even more challenging to solve. Dynamic routing is an example of such an optimization problem [43].

Evolutionary algorithms (EA) are generic meta-heuristic optimization algorithms [44], where the solution to the problem being addressed evolves over time. Swarm intelligence (SI) algorithms are population based evolutionary algorithms, inspired by natural/biological evolution processes (like mutation, selection, survival of the fittest, cross-over etc) or social learning behaviour of the species. In the past decade or so, SI schemes have become increasingly popular and have successfully been used to effectively solve both static and dynamic NP-hard optimization problems. The application areas of SI schemes ranges far and wide in different disciplines of science and industry e.g. communication networks, biomedical, combinatorial optimization, electronics and electromagnetic, graphics and visualization, prediction, neural networks, robots, scheduling, signal processing and many more. This chapter introduces well known swarm intelligence based heuristic algorithms and their effectiveness for solving NP-hard (Nondeterministic Polynomial time – hard) optimization problems.

## 3.1. Swarm Intelligence based Heuristic Algorithms

Traditional mathematical optimization techniques like Integer Linear Programming (ILP), Graph Colouring etc, become very inefficient for solving large NP-hard optimization problems. The computational time and power required, prevents them from producing optimized solutions in a dynamic environment due to the time limitations. Therefore different heuristic algorithms are used to solve NP-hard optimization problems. Swarm Intelligence algorithms are heuristic search methods that mimic the metaphor of natural biological evolution and/or the social behaviour of species [45]. Examples of biological evolution processes are cross-over, reproduction, selection and survival of the fittest etc. Examples of social behaviour are the ability of ants in the colonies to find shortest path to the source of food or the ability of the flock of birds or school of fish to find path to destination. In SI algorithms, a 'swarm' is a collection of non-sophisticated members which cooperate with each other to perform complex tasks [46, 47]. Ant Colony Optimization (ACO), Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are well known and very successful swarm intelligence based evolutionary optimization algorithms. Yet there are many more application based on the principles of swarm intelligence which can be found in [46, 48 and 49].

### 3.1.1. Ant Colony Optimization (ACO)

ACO algorithm was developed by Dorigo et al. [50, 51 and 52], inspired by the foraging behaviour of the ants in the colony to find shortest path between their nest and a source of food. ACO is a population based algorithm which consists of a collection of mobile agents called ants. Each member of the population communicates with each other through the environment in a distributed fashion by laying and following pheromone trails. This phenomenon of cooperation between the ants is called *stigmergy* and enables natural ants to find the shortest path between nest and food source. Similarly in ACO, artificial stigmergy facilitate ants to communicate and cooperate with each other to find solution to the problem being addressed.

In ACO system, each ant incrementally (step by step) constructs a solution for the problem being addressed. Initially, each ant searches the problem space randomly. Then based on its personal performance and problem characteristics, it indirectly communicates with other ants by laying pheromone trails [53]. This local information is used by other (following) ants to make decision at each incremental step during their own solution construction. The decision regarding next move forward is determined by the strength of the pheromone trail, as the ants tend to follow the way having more pheromone trail strength. In other words, the better the solution, the more will be the chance that the same move will be made by other following ants in the colony, and thus will increase the amount of pheromone incrementally. To ensure diversity among candidate solutions, the strength of the trail evaporates over time. Therefore, it enables ants to explore other solutions in the problem search space. The pseudo code for ACO algorithm is given in figure 3.1.

```
procedure ACO_MetaHeuristic

- Initialization
-Place all ants in the initial positions
- For each ant do while (not termination)
        - Construct a complete solution by moving ant.
        - Select each move based on the intensity of pheromone
        trails and problem constraints.
        - Update the intensity of trails i.e. pheromone trail updation,
        based on the quality of the solution;
end do while

end procedure
```

**Figure 3.1: Pseudo Code for Ant Colony Optimization Algorithm**

A comprehensive discussion, detailed performance analysis and discussion about different application areas for ACO algorithm can be found in [46, 49, 54 and 55]

### 3.1.2. Genetic Algorithm (GA)

Genetic Algorithm is an evolutionary search scheme, inspired by the natural/biological evolution processes of a species [45] like reproduction, crossover, selection and survival of the fittest. A genetic algorithm is a population based algorithm where each member of the population (swarm) is called a '*chromosome*'. Each chromosome represents a candidate solution to the problem being addressed. Genetic algorithms start by initializing all the chromosomes in the population. In a single iteration, a set of new chromosomes are produced to be included in the next generation of swarm members. For this purpose, current members of the population undergo operations like 'crossover' and 'mutation'. A fitness function is used to quantize the quality of solution represented by each chromosome. The chromosomes having a poor fitness value which is below a certain limit are excluded from the next generation. This process continues until either the whole swarm converges or till the given number of iterations is completed. Pseudo code for a GA algorithm is given in figure 3.2. Detailed analysis of GA, and its use for solving different NP-hard problems can be found in [56, 57, 58 and 59]

```
procedure GA_Metaheuristic

    Initialize chromosomes
    Evaluate fitness of each chromosome in the swarm

    while (not_termination)
        - Select the chromosome having best fitness value for
        reproduction
        - Reproduce new chromosomes through 'crossover' operation
        - Reproduce new chromosomes through 'mutation' operation
        - Evaluate fitness of each new chromosome
        - Replace least-fit chromosomes in the swarm with these new
        ones.
    end while

end procedure
```

**Figure 3.2: Pseudo Code for Genetic Algorithms**

### 3.1.3. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) was originally developed by Kennedy and Eberhart [60, 61]. It is an evolutionary, population based, optimization algorithm inspired by animal social behaviour e.g.: A flock of birds or a school of fish [48]. It is based on the notion that simple local interactions often lead to complex global behaviours. In a PSO algorithm, each member of the population (swarm) is called a *particle*. Each particle has a position and a velocity. The position of the particle represents a candidate solution to the problem being addressed. The velocity is used to move the particle from one position to another position. PSO algorithms start by initializing all the particles in the swarm. A fitness function is used to quantize the quality of the solution represented by each particle. The particle having the best fitness value in the swarm is marked as the 'global-best' particle. The swarm can further be divided into sub-swarms called local neighbourhoods. The particle having best fitness value in each neighbourhood is marked as the 'local-best' particle. In a single iteration, for each particle, new velocity is computed based on the positions of the global-best (or local-best) particles. Then that velocity is applied to the particle. As a result of that, the particle moves to some other new position thus representing another candidate solution for the problem being addressed as shown in the figure 3.3.

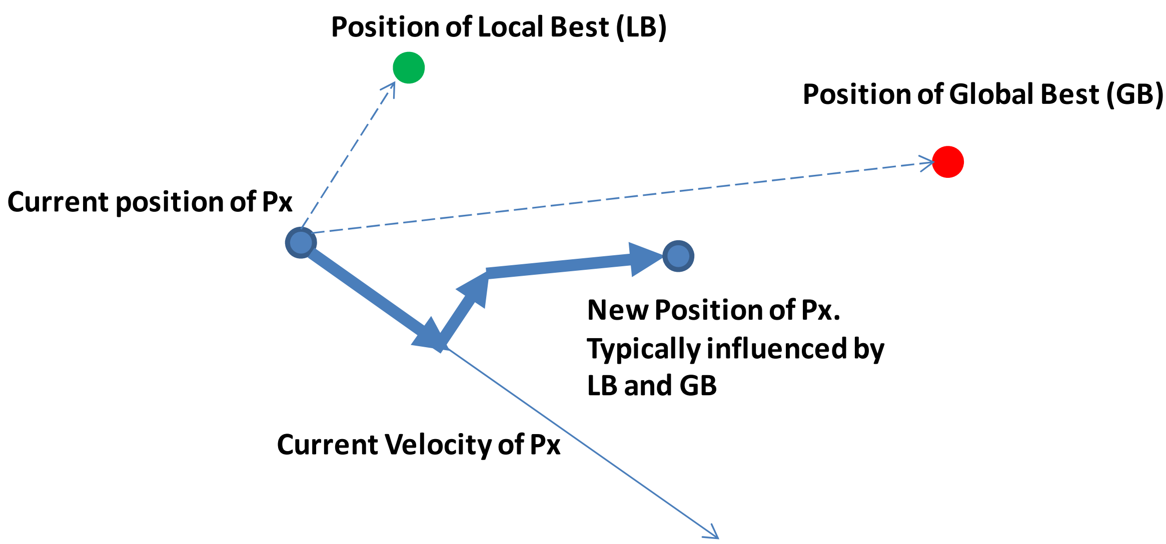


**Figure 3.3: Velocity computation and position updating of a particle Px.**

The magnitude of this move is a function of the current position of the particle and the distance between itself and the best particle in the neighbourhood (local-best / global-best particle). Particles continue to move around the problem search space trying to better themselves in comparison with their own performance and that of their neighbours. This process continues until either the whole swarm converges or till the given number of iterations completes. Generalized pseudo code for a PSO algorithm to solve any problem is given in figure 3.4.

```
procedure PSO_metaheuristic

        - Initialize the particles
        - Quantify each particle's fitness using a fitness function.
        -The particle having best fitness value will be marked as GLOBAL
        BEST, and the particle having best fitness value in the
        neighbourhood will be marked as LOCAL BEST particle.

For each particle Do:
        - Find its velocity according to Global best and/or local best particle.
        - Apply the velocity to the particle.
        - After this, the particle will move to another (new) position.
        - Then re-apply fitness function to update the Global/Local best
        particles.
Iterate until optimal solution or solution of desired quality is not found.

end procedure
```

**Figure 3.4: Pseudo Code for Particle Swarm Optimization.**

In PSO, each particle keeps a record of the best position it has traversed over the problem space, so far. This position is called 'personal-best' position of the particle. This way, particle not only does its own search, it also learns from the search done by the particle having best fitness value in the swarm (or sub-swarm). The "classical" PSO equations, where the position and velocity represents physical attributes of the particles, are represented by equation (3.1) and (3.2).

Velocity for a single particle in the swarm is computed as:

$$V_{id} = V_{id} + \eta_1 r_1 (P_{id} - X_{id}) + \eta_2 r_2 (P_{id}^n - X_{id})$$
$$where \quad i = 1,2,...N.\ d = 1,2,...D \qquad \text{Equation (3.1)}$$

"Moving" a Single Particle in a Swarm

$$X_{id} = X_{id} + V_{id} \qquad \text{Equation (3.2)}$$

$P_{id}$ is the personal-best position, a particle has reached so far.
$P_{id}^n$ is the global-best position of all the particles.
$\eta_1$ (the self-confidence factor) and $\eta_2$ (the swarm-confidence factor) are positive constants called '*acceleration constants*' to determine the influence of $P_{id}$ and $P_{id}^n$;
$r_1$ and $r_2$ are independent random numbers in the range [0, 1].
N is the total number of particles in the swarm
D is the dimension of the problem search space

Equation 3.1 shows that, the value of new velocity of the particle is determined by three main factors, which are:
(1) Momentum
(2) Cognitive learning
(3) Social learning

Momentum is used to move the particle in the direction it has already been travelling [46]. '$\eta_1$' (self-confidence factor or cognitive-learning factor) determines the influence of *exploration* i.e. the search done by particle itself over the problem search space. This factor incorporates the movement of the particle towards the best position it has searched so far. '$\eta_2$' (swarm-confidence factor or social-learning factor) determines the influence of *exploitation* i.e. the search done by the other members of the swarm. This factor incorporates the movement of the particle towards the best position of the global-best (or local-best) particle in the swarm.

Earlier analytical studies on PSO have shown that using the general PSO equation for velocity computation can result in escalating velocity values, especially when the current particle is far from the global-best or local-best particle in the swarm. These large velocity values can lead to premature convergence of the swarm or can accelerate particles beyond the problem search space. To avoid this, different schemes have been proposed in the literature. The simplest of this is a scheme called *'velocity clamping'* which limits the maximum value of the particle's new velocity during velocity computation [62]. For example: Clerc [63] proposed the use of *'constriction factor'* to effectively avoid large values of velocity. Analytical studies of different schemes to restrict the particles stepping out of the problem search space can be found in [62, 64, 65, 66 and 67].

PSO algorithm explores the problem space by adjusting 'trajectories' of individual particles in the swarm as they are conceptualized as moving points in multi-dimensional space [68]. The magnitude of trajectory adjustment depends on the tendency of a particle to be attracted towards its personal-best position or the position of the best particle in the neighbourhood [69]. Ozcan and Mohan [70, 71] analyze the trajectory of particles in a simple PSO system and observe that in traditional PSO, particles 'surf' the search space on sine waves. Some empirical studies have indicated that the traditional PSO algorithm converges significantly faster without effectively exploring the problem search space and suffer from problems like premature convergence towards a local optimal solution [72, 73]. Theoretical analysis and studies on working of PSO systems and impact of different algorithmic parameters on swarm convergence can be found in [74, 75 and 76].

## 3.2. Comparison between different Swarm Intelligence Algorithms (PSO vs GA vs ACO)

PSO has successfully been used to solve many industrial and engineering optimization problems in the diverse areas including biomedical, communication networks, prediction, neural network, graphics and visualization, signal processing, electronics, antenna design, modelling, fuzzy and neuro-fuzzy logic, prediction and forecasting, scheduling, robotics etc. [77] provides a detailed analysis of publications on the application of PSO in different fields of engineering and technology. Some of the advantages of using PSO algorithm are that it:

- Is a Simple concept
- Is an easy implementation of a problem search algorithm
- Possesses fewer algorithmic parameters to adjust than other evolutionary algorithms like genetic algorithms.
- Is robust in terms of controlling parameters
- Is computationally efficient

Different comparative studies have been carried out to analyze the effectiveness of using PSO compared to other evolutionary algorithms. GA and PSO are similar in the way that both techniques are population-based search schemes that mimic the natural biological evolution and/or the social behaviour of species [45, 78]. Each member of the population represents a candidate solution to the problem addressed, and over time they evolve to represent some other candidate solution.

One advantage of PSO over GA is that PSO is more computationally efficient [78, 79]. Mouser and Dunn [80] conclude that PSO not only performs better in terms of solution quality compared with GA, it is also much easier to configure. The main reason for this is that fewer algorithmic parameters are involved in PSO relative to other swarm intelligence based algorithms. In GA, the fitness function is used to determine which member of the population will stay in the next generation and which will be excluded. This requires the need for careful design of the fitness function. In PSO, there is no selection operation based on the fitness function. Rather, each member of the population evolves towards a better solution through an iterative process. So there is always a chance that a member of the population having a poor initial fitness value, will evolve over time to become the best member in the entire population.

In [45] a performance comparison is performed between different swarm intelligence algorithms for two benchmark continuous optimization test problems and concludes that the PSO method was generally found to perform better than other algorithms in terms of solution quality and success rates. PSO also performs better compared to GA and ACO in terms of computation time. One disadvantage of ACO compared to PSO is its slow convergence towards optimal/near-optimal solution [69]. Unlike ACO, in PSO no pheromone table needs to be maintained for next move decision-making. In [82] and [83], evolutionary algorithms are used for feature extraction and classification respectively and conclude that PSO performs relatively better compared to ACO algorithms. Performance comparison studies between PSO and other evolutionary schemes also have been reported in [78, 79, 80, and 81].

# CHAPTER 4 ROUTING AND WAVELENGTH ASSIGNMENT

Wavelength routing optical networks are mainly deployed as back-bones for long-haul networks e.g. nationwide coverage [4] and metro-area networks in order to cope with ever-increasing amount of traffic originating from bandwidth hungry applications, services and increasing number of users. Access nodes connect with the optical back-bone through wavelength sensitive routing/switching nodes (edge nodes). Access nodes here do not necessarily mean single terminal equipment, but can also be an aggregate activity from a collection of terminals or multiple edge devices like ATM switches and IP routers as shown in the figure 4.1.

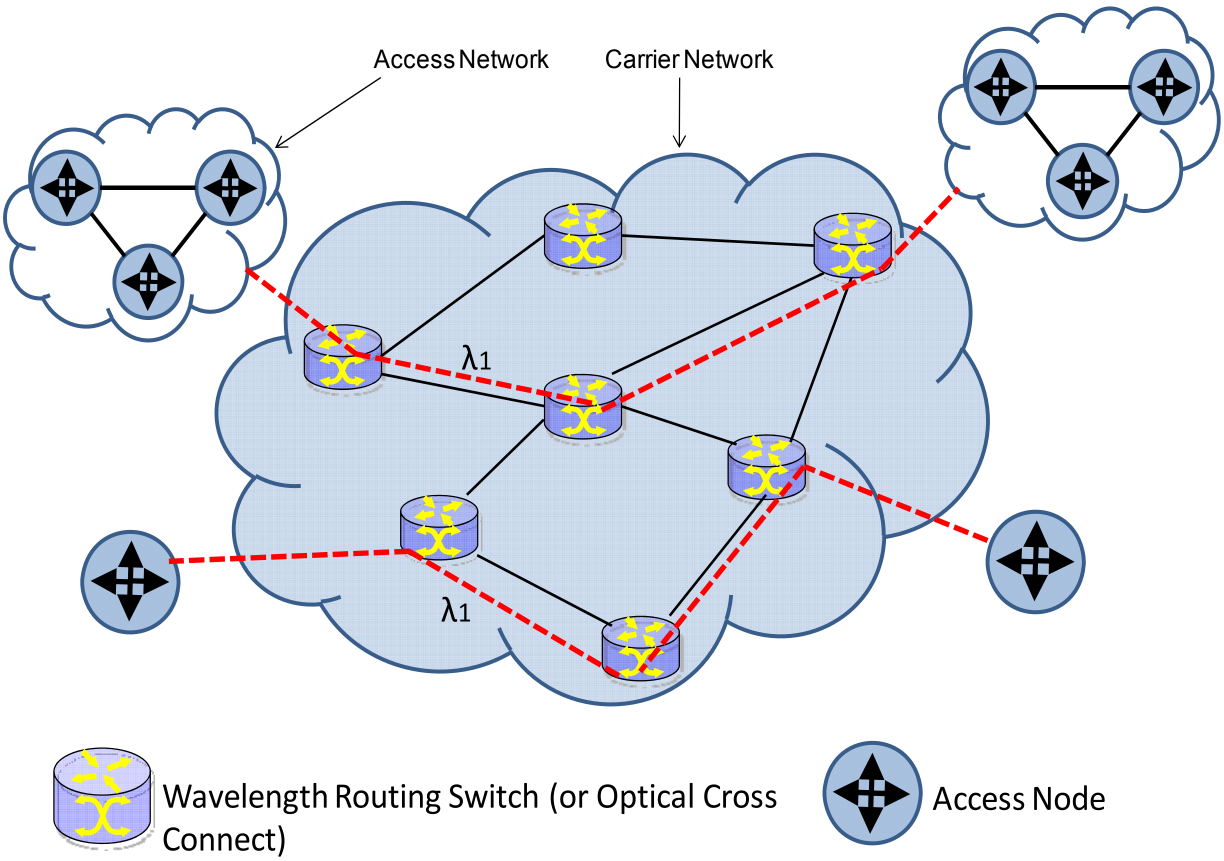


**Figure 4.1: Lightpath routing in all-optical wavelength routing WDM back-bone network.**

In wavelength routing all-optical networks, access nodes (end users) communicate with each other by setting up all-optical channels called lightpaths between them (The term lightpath and connection is used interchangeably here, as setting up a connection between source-destination nodes requires establishing a lightpath between them). A lightpath can traverse multiple optical link fibres in order to provision a circuit switch connection between source and destination access nodes; however, the information sent by the lightpath does not undergo Optical-Electrical-Optical conversion at intermediate nodes.

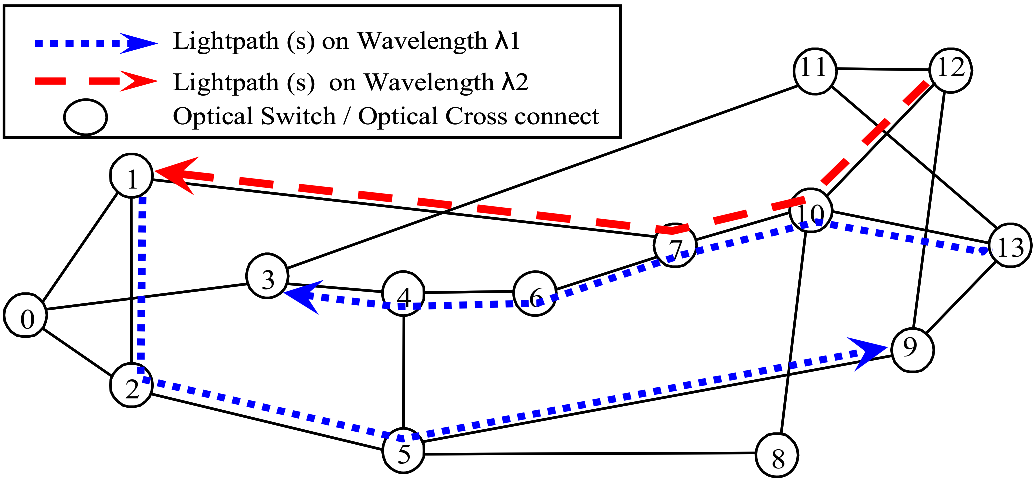


**Figure 4.2: Wavelength Routed WDM Optical Network (NSFNET) with lightpath connections.**

Establishment of lightpaths creates a logical topology on top of the physical topology of a WDM optical network. If the intermediate nodes along the route, chosen for lightpath setup, are not equipped with wavelength-conversion capability, then same wavelength needs to be assigned to the lightpath over all the fibre links. This property is called the *wavelength continuity constraint*. Two lightpaths sharing a common edge of the network need to be assigned unique wavelengths. This is called the *"wavelength clash constraint"*. As shown in figure 4.2, the routes 13→3 and 1→9 are assigned the same wavelength (λ1) because these two lightpaths traverse different edge disjoint routes. However routes 12→1 and 13→3 must be assigned different wavelengths, because these two lightpaths traverse a common edge (10, 7) where these two need to be assigned a distinct wavelength in order to satisfy the *"wavelength clash constraint"*.

Typically, connection requests to setup lightpaths can be categorized into following types:
(1) Static connection requests
(2) Scheduled connection requests
(3) Incremental requests
(4) Dynamic requests

In *static requests*, all the connection requests are known in advance. In s*cheduled lightpath requests*, all the connection requests plus their set-up and tear-down times are also known in advance. In *incremental lightpath requests*, connection requests arrive one-by-one, without any prior knowledge, and will stay in the network for an indefinite time [6]. In *dynamic lightpath requests*, connection requests arrive unexpectedly without any prior knowledge, and after lightpath setup, they will stay in the network for a finite amount of time.

In wavelength routed networks, the *physical topology* is defined by the end-nodes, wavelength routers and the optical fibres connecting them. The source node needs to setup a lightpath to the destination for data transmission on top of the physical topology. The lightpath setup over the network for the transfer of data will constitute a logical topology. To set up a lightpath, an appropriate route from source to destination node and a unique wavelength needs to be assigned. The problem of finding an appropriate route and wavelength for setting up a lightpath is known as the *Routing and Wavelength Assignment problem (RWA)*. In static and scheduled lightpath connection requests, the objective of the RWA problem is to setup a lightpath for each connection request in a globally optimal fashion while minimizing the network resources required. In the case of incremental and dynamic traffic, the objective of RWA problem is to setup a lightpath for each connection request such that the blocking probability for future connection requests is minimized. On the basis of objectives, the RWA problem can be categorized as the static RWA also know as Static Lightpath Establishment (SLE) problem and the Dynamic RWA also known as Dynamic Lightpath Establishment (DLE) problem.

## 4.1. Static Routing and Wavelength Assignment

In this section static routing and wavelength assignment (static RWA) (also known as the Static Lightpath Establishment (SLE)) for wavelength routed optical networks with wavelength continuity constraint, is addressed. In static RWA, all the connection requests that need to be setup over the network are known in advance. Static RWA is NP (Nondeterministic - polynomial time) hard optimization problem [7] and is carried out offline. The objective is to minimize the number of wavelengths required to setup lightpaths for a given set of connection requests. Alternatively, the objective of static RWA can be defined as maximizing the number of lightpaths that can be setup from a given number of wavelengths.

The solution of static RWA process results in a virtual topology of lightpaths which is to be embedded onto the physical topology of the network of optical fibres and OCXs. Therefore, static RWA is also referred to as the *virtual topology design* problem [84, 85 and 86]. Usually in these techniques, each edge of the virtual topology represents a lightpath connection between source ‘s’ and destination ‘d’ while the shape of the virtual topology must conform with the physical connections of the networks.

The static RWA problem raises the issue of *fairness* because the solution to this problem will tend to establish more short connections, which traverse fewer fibre links than long connections that traverse a greater number of links [6].

The static RWA problem can be logically divided into four sub-problems [87].

(1) Topology sub-problem; this determines the logical lightpath topology which needs to be provisioned over the physical network.
(2) Lightpath routing sub-problem; this determines the route for each lightpath over which lightpath is to be established in the physical network.
(3) Wavelength assignment sub-problem; this determines the appropriate wavelength for each lightpath to be provisioned over the network.
(4) Traffic routing sub-problem; this routes the packet traffic between source and destination nodes over the network.

The different schemes which address the static-RWA problem can be divided into three different domains:

(1) Schemes which solve all four logical sub-problems together to compute a typically near-optimal solution
(2) Schemes which addresses a specific subset among these four sub-problems
(3) Schemes which addresses the issue of mapping of different logical topology designs onto the physical topology of the network

The work in this thesis addresses the issue of solving routing sub-problem and wavelength assignment sub-problem while strictly conforming to the physical architecture of the underlying network adhering to the wavelength constraints. This results in a valid solution (virtual topology design) which can always be mapped onto the physical underlying network.

### 4.1.1. Integer Linear Programming (ILP) Formulation:

The static RWA problem can be formulated as a multi-commodity flow problem with integer flows in each link. The objective function in this case is to minimize the flow in each link, which, in turn, corresponds to minimizing the number of lightpaths passing through a particular link in the physical network [88]. Since each lightpath, traversing a particular link in the network needs to be assigned a unique wavelength in order to satisfy 'wavelength clash constraint', the objective function therefore minimizes the number of wavelengths required for establishing all the lightpaths in the given set for a given physical network.

In order to formulate static RWA problem for wavelength continuous, single fibre WDM network, a given set of connection requests is assumed. Each element of this set is represented by the variable '$\lambda_q\ (s, d)$' where 's' represents the source node-number and 'd' represents the destination node-number'. Between every source destination '$(s, d)$' node pair, multiple connection requests can exist where this multiplicity is represented by the variable '$q$'. Each wavelength supported by the fibre link is identified by a wavelength-number '$w$'. The physical topology link (bi-directional) between two nodes is represented by the $E\ (m, n)$, where 'm' and 'n' represent the node-numbers of the end node of the link.

Let,

(a) $\lambda_q$ *(s, d)* = 1 if there exists q[th] connection request between source node ‘s’ and destination node ‘d’ in the given set of connection requests. Where, q = 0, 1, 2 ... Q and ‘Q’ is the maximum number of connection requests allowed between any specific source-destination pair.

(b) $L^{(w,\ q)}(s,\ d)$ = 1 if the q[th] lightpath between source ‘s’ and destination ‘d’, use wavelength ‘w’; else $L^{(w,\ q)}(s,\ d) = 0$

(c) $L_{(m,\ n)}^{(w,\ q)}(s,\ d)$ = 1 if the q[th] lightpath between source ‘s’ and destination ‘d’, use wavelength ‘w’ and is routed through physical link (m, n); else $L_{(m,\ n)}^{(w,q)}(s,\ d) = 0$

(d) $F_{max}$ = Maximum number of lightpaths traversing over any particular physical link (m, n) in the network.

(e) $E_{(m,\ n)}$ = 1 if there exists a link in the physical topology between nodes ‘m’ and ‘n’.

An Integer Linear Program (ILP) formulation [86] can be written as:

**Minimize:** $\boldsymbol{F_{max}}$ Equation 4.1

Such that:

$$F_{\max} \geq \sum_{s,d} L_{m,n}^{(w,q)}(s,d) \quad \forall m,n$$

Equation 4.2

$$\sum_{w}\sum_{m} L_{m,n}^{(w,q)}(s,d)E_{m,n} - \sum_{w}\sum_{m} L_{n,m}^{(w,q)}(s,d)E_{n,m}$$

$$= \begin{cases} \lambda_q(s,d) \quad if\ m = d \\ -\lambda_q(s,d) \quad if\ m = s \\ 0 \quad if\ m \neq s\ and\ m \neq d \end{cases}$$

Equation 4.3

Equation 4.3 is *conservation of wavelength equation* to ensure that a wavelength is conserved at every node for every $\lambda_q$ *(s, d)* i.e. there is a path in the physical topology of the network from node ‘s’ to node ‘d’ with wavelength assigned to it. This equation is analogous to a ‘flow conservation equation’ in multi-commodity flow problems.

$$\sum_{w=1}^{F_{\max}} L_{s,d}^{(w,q)} = \lambda_q(s,d) \quad \forall (s,d)\ and\ 'q'$$

Equation 4.4

Equation 4.4 is called *unique wavelength constraint* and ensures that the wavelength used by the lightpath is unique.

$$L_{m,n}^{(w,q)}(s,d) \le L^{(w,q)}(s,d) \quad \forall (s,d),(m,n),'q'\ and\ 'w'$$

Equation 4.5

Equation 4.5 is called *wavelength continuity constraint* and ensures that the same wavelength is assigned to the lightpath over all the links which it traverses.

$$\sum_{q} \sum_{(s,d)} L_{m,n}^{(w,q)}(s,d) \le 1, \quad \forall\ (m,n)\ and\ 'w'$$

s

Equation 4.6

Equation 4.6 is *wavelength clash constraint* and ensures that two lightpaths traversing over a particular edge in the network are not assigned the same wavelength.

### 4.1.2. Static RWA Problem Search Space Size:

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. Consider an example of 14 nodes, 21 edges variant of NSFNET shown in figure 4.2, and an average of 5 unidirectional lightpaths per node (source as well as sink). For simplicity, assume the value of ‘q’ is 1. Then we have:

- Number of Equations 4.1 ($F_{max}$ variables) = 1.
- Number of Equations 4.2 (Edges) = 21.
- Number of Equations 4.3 (14 Nodes per each *‘s-d’* pair) = 14 * 182 = 2548
- Number of Equations 4.4 ($\lambda_q$ *(s, d)* variables) = 14 * 13 * 1 = 182 *‘s-d’* pairs.
- Number of Equations 4.5 ($L_{(m,n)}^{(w,q)}$ *(s, d)* variables) = 182 *‘s-d’* pairs * 21 edges = 3822.
- Number of Equations 4.6 = 21
- Total Number of Equations = $[1 + 21 + 2548 + 182 + 3822 + 21]^2 = (6595)^2$

The generalized form of ILP is computationally expensive and can overwhelm the available computing capabilities [86], even for moderate sized networks. Therefore, in order to decrease the computational complexity, different problem space size pruning techniques are used like randomized rounding and path stripping. Example search space reduction schemes can be found in [88]. Even after applying problem-space reduction techniques, solving static RWA using ILP is computationally expensive and typically requires a large execution time.

In order to decrease the computational requirements and time to solve NP-hard optimization problems, different stochastic and heuristic algorithms such as *greedy search*, *tabu search*, *local search*, *simulated annealing*, *stochastic diffusion search*, *swarm intelligence algorithms* (like ant colony optimization, genetic algorithms, particle swarm optimization) and many more have been used successfully. Unlike mathematical problem search space algorithms such as ILP, heuristic algorithms do not guarantee an *optimal solution* to the problem domain. In the case of problem domains with a large search space, it is difficult to ensure the quality of the final solution provided by these schemes. However, such schemes are suitable in environments where a solution is required in a short time compared to mathematical schemes like ILP and graph colouring. Each heuristic technique has its own advantages and disadvantages and the efficiency of applying a particular technique depends on many factors like the computational complexity, execution time, quality of solution, robustness and so forth.

### 4.1.3. Related Work:

Most of the stochastic, heuristic or mathematical problem search space approaches used to solve the static RWA problem, divide it into two sub-problems; the *routing sub-problem* and the *wavelength assignment sub-problem*, and try to solve each separately. An overview of well-known static RWA algorithms, their functional classification, advantages and disadvantages can be found in [89]. In [88] the static RWA problem is divided into routing and wavelength sub-problems and is solved independently. For solving the routing sub-problem, a multi-commodity flow formulation is used. For reducing the size of problem search space, randomized rounding is employed. The wavelength assignment sub-problem is solved using a graph-colouring technique. In [88], when the number of alternative paths is kept equal to one, the LP solver achieves optimal solution for static RWA problem. For problem instances where the number of alternative paths is assumed to be greater than one, LP solver fail to reach optimum solution. Also, the time taken to solve linear program increases rapidly as the number of connections is increased. Some instances of the static RWA problem cause the LP solver fail to produce any result because the computing resources were overwhelmed with the computational complexity of underlying algorithm. A generalization of the graph colouring problem, called the partition colouring problem, and its application for solving static RWA in WDM all-optical network is proposed in [90].

[91] propose a Tabu Search (TS) based heuristic scheme for solving static RWA problem. Both routing and wavelength assignment sub-problems are solved collectively. The TS based static RWA solver achieves near-optimal (and at times sub-optimal) solution when compared with ILP. However, the main advantage of this heuristic scheme is reduction in execution time compared to ILP. In [92], the authors used an iterative algorithm based on local random search for finding a reasonably good route. To assign an appropriate wavelength, a greedy graph colouring and a TS algorithm are employed. Simulation result show that the running time of TS algorithm increases much faster than the running time of greedy algorithm, as a function of number of nodes in the network. [92] concluded that the performance of the purposed scheme can be significantly improved by employing improved route selection algorithm.

A unified heuristic approach to solving the static RWA task is proposed in [93] where both routing and wavelength assignment sub-problems are solved simultaneously using an integer formulation and a column generation technique. [93] concluded that though the proposed scheme provide *probably* good solution in reasonable time, but don't guarantee an optimal or even near-optimal solution. In [94] static RWA is solved using a genetic algorithm where members of a population called chromosomes, use genetic operators to generate new members and then members are selected for the next generation based on a fitness function. The results obtained from using genetic algorithm in [94] are comparable to the solutions obtained with heuristic algorithms like first-fit. However, they are far away from the optimal solution. In [95, 96], Ant Colony Optimization (ACO) algorithms are used to minimize the number of wavelengths required to provision all the given connection requests. The disadvantage of such ACO based heuristic algorithm is their higher computational cost resulting in high execution time and the large number of algorithmic parameters involved. In order to characterize the quality of solution provided by these heuristic algorithms, different bounds for the static RWA problem and the theoretical considerations involved in deriving them can be found in [84]

## 4.2. Dynamic Routing and Wavelength Assignment:

In section 4.1 concerning static routing and wavelength assignment, all the lightpath requests which need to be set up over the physical topology of the network are known in advance. Mathematical techniques like ILP, graph colouring or other techniques that are computationally and time expensive to search for a global optimum solution can sometimes be used. However in dynamic lightpath establishment, where lightpath requests arrive dynamically on-the-fly, these types of global optimal algorithms become unable to provide a solution in time. In this case, a dynamic algorithm is required that can provision resources for the lightpath request rapidly, and that can adaptively route the future lightpath requests over different routes efficiently.

Under dynamic traffic scenarios, connection requests typically arrive in a random fashion. These connection requests need to be provisioned individually depending on the state of the network in terms of resource availability. The network state changes dynamically whenever a new lightpath is provisioned over the network or some already provisioned lightpath is released (when no longer required). Upon the arrival of a connection request, the dynamic RWA scheme needs to find a route and select an appropriate wavelength for it. If a free wavelength is available over the computed route, the connection can be established. In the case of a lack of resource availability, the connection is considered to be blocked.

Particularly in dynamic situations, it is difficult to solve the routing and wavelength assignment problems simultaneously. To simplify the task, routing and wavelength assignment is usually subdivided into two separate sub-problems namely a routing sub-problem and a wavelength assignment sub-problem. In this section, different strategies used to solve the routing sub-problem are discussed.

### 4.2.1. Fixed Routing:

This is the simplest scheme in which a fixed route is always chosen for a particular source destination connection request. *Fixed shortest path routing* is an example of such an approach [6]. A shortest path route is computed statically for each possible source-destination pair using a shortest path least cost algorithm like Dijkstra or the BellMan-Ford algorithm. Whenever a connection request arrives for a source-destination (s-d) pair, the pre-computed path for this particular "s-d" pair is selected. As shown in the figure 4.3, for a connection request from node '0' to node '2', the same path of 0→1→2 is always chosen.

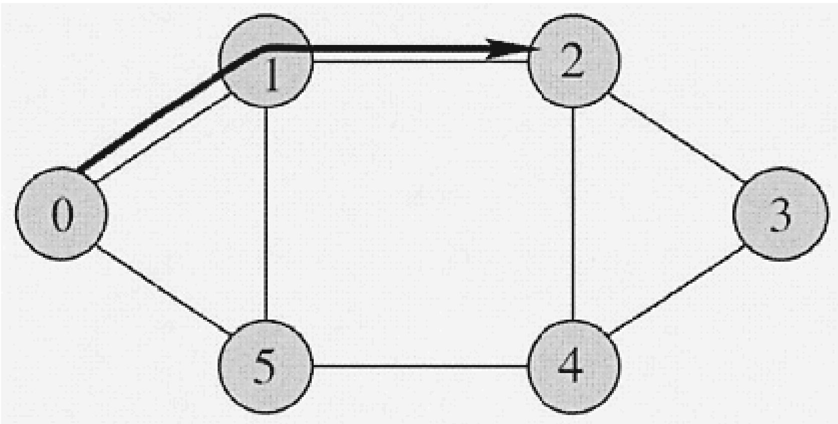


**Figure 4.3: Example of Fixed Routing**

The advantage of fixed routing scheme is its simplicity. However such a scheme can lead to a high blocking probability in the case of dynamic traffic by overloading some of the edges of the network, when most of other edges have free resources available. Suppose, all the wavelengths on the edge from node '0' to node '1' are busy, in this case if a lightpath request from 0→2 arrives; it will be blocked even if all the other edges in the network have free wavelengths available. In the case of static RWA, fixed routing can lead to using more wavelengths than are optimally needed.

### 4.2.2. Fixed-alternate Routing:

To alleviate the problems of fixed-routing, fixed-alternate routing is used to choose an appropriate path for the connection request. In this scheme, instead of pre-computing just one fixed route for each source-destination (s-d) pair, a number of paths are pre-computed for each s-d pair. The pre-computed *K-shortest path* algorithm is an example of such a scheme.

In this case, even if all the edges have no free resources available on the primary path, other pre-computed paths are consulted before blocking the connection request. As shown in the figure 4.4, for a connection request from node '0' to node '2', the two fixed alternate routes are 0→1→2 and 0→5→4→2.

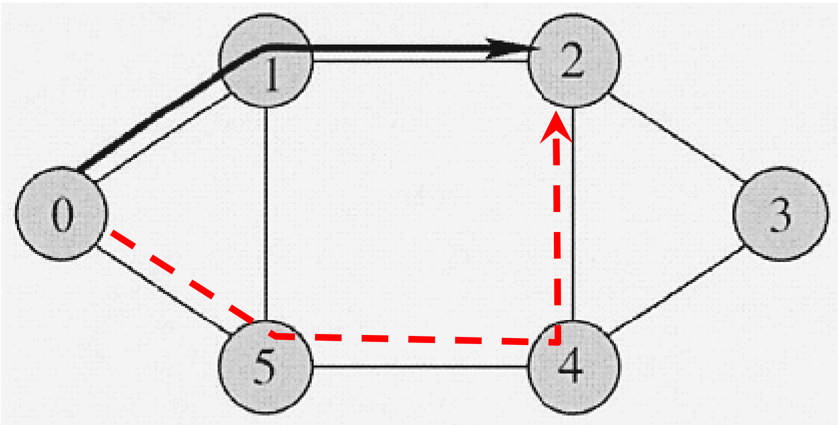


**Figure 4.4: Example of Fixed Alternate Routing**

Fixed-alternate routing shows better performance for both static and dynamic RWA compared to fixed routing. It has the same advantage of simplicity as that of fixed routing, because all the routes are pre-computed. However, it shows significantly better blocking probability. It has also been shown that for certain kinds of network, fixed alternate routing having as few as just two alternate routes shows lower blocking probability than having full wavelength conversion at each node with fixed routing [6]. Since in both these strategies, the decision to choose a route is made based on pre-computed paths, independent of the current network state, this can lead the network into a non-optimal state.

### 4.2.3. Adaptive Routing:

In adaptive routing, for each connection request, an appropriate route is computed on-line depending on the state of the network taking into account failures or congestion. The network state is also dynamically determined by the connections already setup over the network. *Least-cost-path* routing is an example of adaptive routing. In adaptive routing, a connection request is blocked only if no route exists from the source to destination node. Since adaptive routing takes into account the state of the network, it results in lower blocking probability compared to fixed and fixed-alternate routing. For example suppose the edges (1, 2) and (2,

4) are busy and have no free resources available (i.e. wavelengths in the case of a WDM network). Even in this case, adaptive routing can find a route between node 0 and node 2 as shown in the figure 4.5.

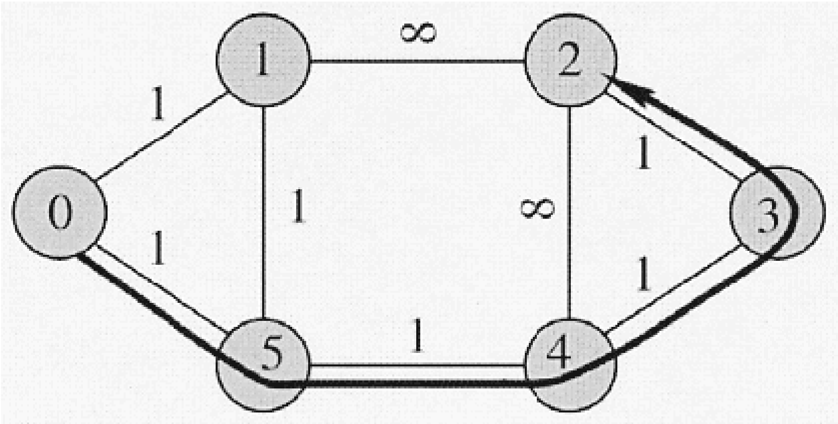


**Figure 4.5: Example of Adaptive Routing**

A disadvantage of adaptive routing is the computational complexity, because for each connection request, a route needs to be computed on-line.

### 4.2.4. Related Work:

[97] has used a simple heuristic approach of selecting the least congested route from the set of alternative routes between a source-destination pair for dynamic lightpath establishment. A first-fit algorithm is used for the wavelength assignment. If the order in which connection requests arrive is kept the same as that of the static traffic case, this approach gives close results between statically optimized RWA using randomized rounding and dynamic RWA [4]. However, as the congestion increases over the links in the network, the difference between static RWA and dynamic RWA increases as this least-congested path approach uses more wavelengths on each link as compared to the static RWA [97] case. The performance of such an approach depends on the order in which connection requests arrive, the connection request arrival rate and the connection holding time. In [98] a *fixed path least congestion* approach is proposed that uses congestion and neighbourhood information to compute a route for each lightpath request. In [99] a *hybrid fixed paths least congested* approach is used which combines the benefits of both fixed alternate routing and adaptive routing. When a lightpath request arrives, all the links of each pre-computed path are classified according to the number

of free wavelengths available. The first k-links for each pre-computed paths are evaluated. The path chosen will be the one that has greatest number of idle wavelengths along its first k-links analysed.

### 4.2.5. Wavelength Assignment sub-problem:

After selecting a route for the connection request, an appropriate wavelength needs to be assigned to setup a light path from source to destination nodes. For static RWA, optical techniques like graph colouring are used to do wavelength assignment. For dynamic connection requests, different heuristic algorithms are used for dynamic lightpath establishment like Random, First-Fit, Least-Used (spread), Most-Used (pack), Min-product, Least Loaded, MAX-SUM, Relative Capacity Loss, Wavelength Reservation and Protecting Threshold. Each heuristic algorithm has its own advantages and disadvantages. Detailed analysis and comparison among these wavelength assignment algorithms can be found in [92, 6].

The efficiency and effectiveness of any dynamic RWA scheme is generally measured in terms of connection blocking probability for the future connection requests. The blocking probability can be simply defined as the ratio of total number of connections being blocked to the total number of connections that have arrived for provisioning. Another important performance parameter is 'fairness' which is referred to as variability in blocking probability among lightpaths between specific source-destination pairs. Several studies have been carried out to observe the effect of different parameters on the blocking probability performance and fairness [100, 101 and 102].

Some of the general conclusions are [87]:

(1) The introduction of a wavelength conversion capability in OXCs can significantly improve the fairness but the impact of this on the blocking probability performance is not significant.

(2) Alternate routing improves the overall blocking probability and fairness performance as the route chosen depends on the current network state in terms of network resource availability.

(3) The First-Fit algorithm is easier and less expensive to implement compared to other wavelength assignment algorithms. It also shows similar blocking probability and fairness performance when compared to more complex wavelength assignment schemes.

# CHAPTER 5 ROUTING AND WAVELENGTH ASSIGNMENT USING PARTICLE SWARM OPTIMIZATION (STATIC TRAFFIC CASE)

Traditional optimization techniques (like ILP) become very inefficient for solving NP-hard optimization problems. The computational time and power required prevents them from producing optimized solutions in a dynamic environment due to the time limitations. Therefore different heuristic and stochastic algorithms are used to solve NP-hard optimization problems. Nature inspired swarm intelligence algorithms like Genetic algorithms (GA), Ant colony optimization (ACO) and Particle Swarm Optimization (PSO) have been used successfully to solve NP-hard problems to produce optimal or near-optimal solutions. These techniques are also classified as evolutionary computation techniques because the solution to the problem evolves through iteration, though the optimal solution is not always guaranteed.

In this chapter, a PSO technique is proposed to solve the Routing and Wavelength Assignment problem (RWA) for static traffic (here after referred to as '*PSO-lb*' scheme), where all the connection requests are known in advance. Some of the novelties of this work are:

- Novel Encoding/Decoding scheme used for representation of position of the particle. A particle here is represented as a vector of route-ids, where each route-id is used to identify a unique route from the set of pre-computed K-Shortest Paths.
- Two novel strategies (referred to as St (1) and St (2)) are devised to prioritize the selection of route-ids during computation of its velocity. These two strategies significantly improve the fitness value of the particle and thus the overall performance of the swarm in PSO-lb scheme.
- Novel use of 'edge usage table' associated with each particle in PSO-lb scheme to help prioritize route-id selection during velocity computation.
- A novel operation (scheme referred to as St (3)) is devised for the global best particle of the swarm. In general PSO schemes, global best particle guide other particle of the

swarm by influencing their movement during their velocity computation and thus in position updating, however, itself don't do any search. The proposed operation of global best particle encourages it to search the problem space along with influencing the movement of the other swarm particles. This novel operation significantly improves the search capability of the PSO-lb scheme.

PSO is a population-based algorithm based on the social psychology metaphor. Members of the population observe other members of the population and try to improve themselves. The whole population of individuals is called the swarm, while each individual is called a particle. In the proposed scheme, the movement of the particles in the swarm is influenced by either the position of the global best particle (particle having best fitness value in the swarm) or the position of the local best particle (particle having the best fitness value in the sub-swarm or local neighbourhood). The neighbourhood for a particle is defined as a sub-collection of particles that are within a certain distance from it. Distance here is defined in terms of degree of similarity in the number of routes between two particles. The size of the neighbourhood is a user-defined parameter.

A particle is an encoding of a candidate solution for the problem being addressed. Every particle has a fitness value that represents the quality of the particle as a solution. When using PSO for solving any problem, first of all particles are initialized randomly or using some suitable scheme. Then fitness function is applied to each particle in order to quantize its fitness. The particle with the best fitness value in the neighbourhood is marked as the local best particle and the particle having the best fitness value in the swarm is marked as the global best. For each particle, its velocity is computed. Then that velocity is applied to that particle. As a result, the particle will move to another position, representing another candidate solution for the problem domain. The magnitude of this move is a function of the current position of the particle and the distance between itself and global best (or local best) particle. Particles continue to move around over problem space in a manner trying to better themselves in comparison with their own performance and that of their neighbours.

Unlike ACO, in PSO no pheromone table needs to be maintained and updating for next hop decision-making. In GA, the fitness function is used to determine which member of the population will stay in the next generation and which will be excluded. This requires the need for careful design of fitness function. In PSO, there is no selection operation based on the fitness function. Rather, each member of the population evolves towards a better solution through the iterative process. So there is always a chance that a member of the population having a bad initial fitness value, will evolve over time to become the best member in the entire population of particles. The generalized pseudo code of PSO algorithm to solve any problem is as follows:

## 5.1. Generalized PSEUDO CODE for PSO algorithm:

The pseudo code for heuristic based, generalized PSO algorithm is as follows:

- Initialize the particles
- Quantify each particle's fitness using a fitness function.
- The particle having best fitness value will be marked as GLOBAL BEST, and the particle having best fitness value in the neighbourhood will be marked as LOCAL BEST particle.
- For each particle Do:
    - Find its velocity according to Global best and/or local best particle.
    - Apply the velocity to the particle.
    - After this, the particle will move to another (new) position.
    - Then re-apply fitness function to update the Global/Local best particles.
- Iterate until optimal solution or solution of desired quality is not found.

## 5.2. Modified PSO Equations for solving RWA

In order to apply PSO for solving the RWA problem, the general PSO equations are modified so that PSO can be mapped for RWA. In the proposed static RWA algorithm, the *velocity* of movement for each particle is either influenced/governed according to global best or local best particle but not both at any one time as shown in equation 5.1. The velocity is then used in the determination of the next position to move to in the solution space where this movement is represented by equation 5.2. In any iteration, the position of the particle is changed either according to the position of the global best particle or local best particle. So the equation to find out velocity for the particle has been modified as follows.

$V_{i+1} = \alpha * C1 (P_{gb} - X_i) + (1 - \alpha) * C2 (P_{lb} - X_i)$ Equation (5.1)

$X_{i+1} = X_i + V_{i+1}$ Equation (5.2)

Where,

$\alpha$ is either 0 or 1

C1 & C2 are social learning parameters and C1 = C2

$P_{gb}$ = Position of global best particle

$P_{lb}$ = Position of local best particle

$X_i$ = Position of current particle.

## 5.3. Representation of particles for RWA problem (Static case – Traffic demand is known in advance):

For each connection request, an appropriate route is selected randomly from pre-computed k-shortest paths, where each route is identified by a unique route-id. Particle is represented as a vector of route ids. E.g. In the case NSFNET (shown in figure 4.2), assume we have eight connection requests. The randomly chosen routes for the given connection request, their respective routes ids and a particle having these chosen routes may appear as shown in the figure 5.1 (a) & 5.1 (b), respectively.

(a)

| Connection # | Connection Request | Chosen Routes | Route Id |
|---|---|---|---|
| 1 | 1→3 | 1→0→3 | R39 |
| 2 | 4→8 | 4→6→7→10→8 | R73 |
| 3 | 9→11 | 9→13→11 | R312 |
| 4 | 12→5 | 12→10→8→5 | R1096 |
| 5 | 9→2 | 9→5→2 | R747 |
| 6 | 6→13 | 6→4→5→9→13 | R201 |
| 7 | 8→7 | 8→10→7 | R627 |
| 8 | 6→0 | 6→4→5→2→0 | R559 |

(b)

| | | | | | | |
|---|---|---|---|---|---|---|
| R39 | R73 | R312 | R1096 R747 | R201 | R627 | R559 |

**Figure 5.1: (a) Connection requests to be provisioned, chosen routes and their corresponding ids. (b) Particle's representation corresponding to the chosen routes.**

With each particle, a *common edge usage table* is attached, which shows the edge usage in terms of routes traversing over an edge in the network. This table will help to determine which edges of the network will be overloaded, if the routes of the current particle are chosen.

## 5.4. How to calculate velocity of a particle:

Equation 5.1 is used to calculate the velocity for any particle. Velocity here is a vector of route-ids that will be replaced in the current particle according to global or local best particle.

- $(P_{gb} - X_i)$ = Routes those are different in the global best particle and current particle.
- $(P_{lb} - X_i)$ = Routes those are different in the local best particle and current particle.
- C1 and C2 represent social learning parameters and will determine the number of routes to be replaced.
- 'α' is used to select whether we will be changing routes in the current particle according to either global best particle or local best particle, but not both in a single iteration for any particle.

To calculate velocity, a straightforward approach is to randomly pick up route-ids from ($P_{gb} - X_i$) or ($P_{lb} - X_i$) vector and include it in velocity vector. However, in the proposed PSO-lb scheme, a novel scheme is used for selection of route-ids from ($P_{gb} - X_i$) or ($P_{lb} - X_i$) vector. For this purpose, edge usage table is used to get information about the degree of congestion on each edge of the network. Velocity here will be a vector of route ids, which indicate the routes to be replaced in the current particle by the corresponding routes in the global best or local best particles. For example: As shown in the figure 5.2(a), let's say particle $P_2$ needs to update its position according to the position of particle $P_1$. The particles $P_1$ and $P_2$ have six different routes (at position 1, 2, 3, 5, 6 and 7) as shown in figure 5.2(b). If the social learning parameter is 0.5, then three routes in $P_2$ need to be replaced by the routes in the $P_1$ (corresponding to the respective connection request). Instead of picking up routes randomly from $P_1 - P_2$ vector, those routes are picked that traverse the most overloaded edges of the networks. According to the edge usage table of P2, let's say route R11, R55 and R81 are traversing the most overloaded edges of the network, and then the resulting new velocity for particle $P_2$ is shown in the figure 5.2(c).

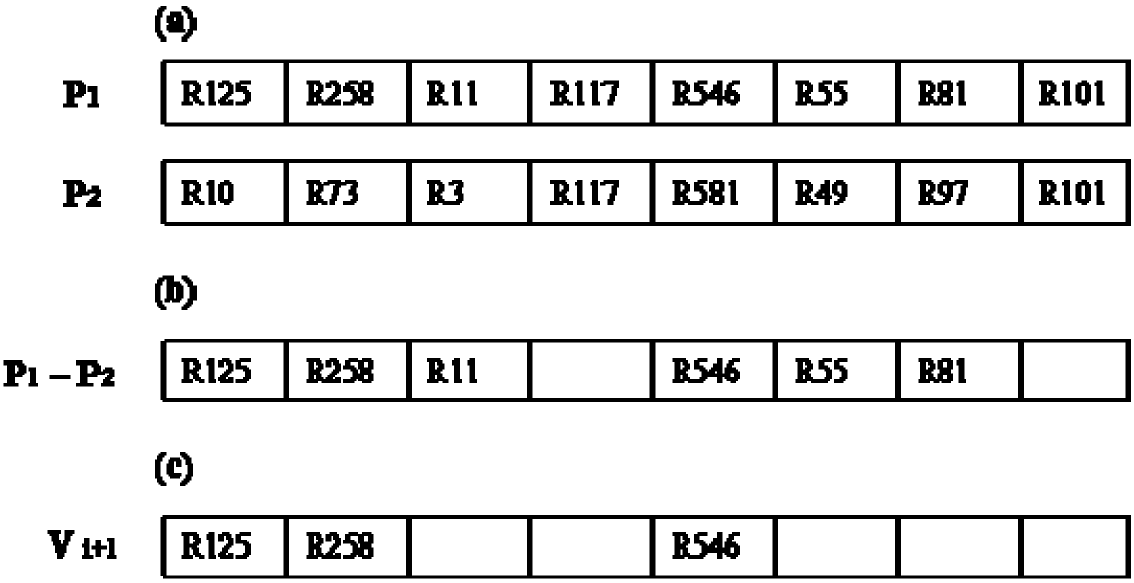


**Figure 5.2: (a) Two particles $P_1$ and $P_2$ (b) Routes in $P_1$ which are different from $P_2$ (c) New velocity for particle $P_2$.**

## 5.5. How to apply velocity to a particle (Redefining '+' operator):

Equation 5.2 is used to apply the velocity calculated, to the current particle so that it can move to a new position. For the RWA problem, the meaning of '+' operator needs to be re-defined. The routes in the velocity vector will replace the corresponding routes in the current particle. For example, as shown in the figure 5.3, the current position of a particle '$X_i$' is represented by route-ids R10, R73, R3, R117, R581, R49, R97 and R101. The new velocity '$V_{i+1}$' computed for the particle '$X_i$' contains three route-ids which are R125, R258 and R546. Application of velocity to the particle '$X_i$' (as illustrated in the figure 5.3) means that these route-ids in '$V_{i+1}$' will replace the corresponding route-ids in '$X_i$'. After application of velocity, the particle moves to a new position '$X_{i+1}$' which now represents some other candidate solution to the problem space being addresses (as illustrated in figure 5.3).

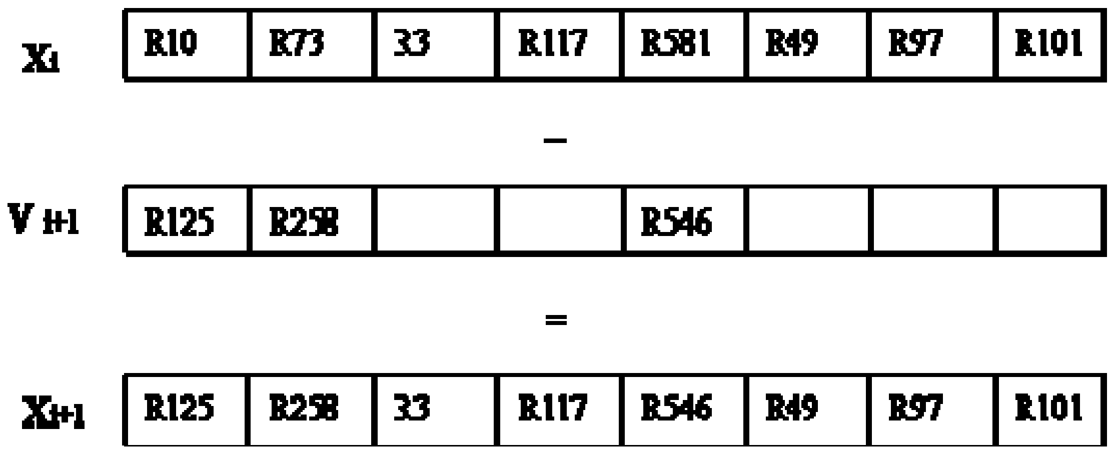


**Figure 5.3: Applying velocity to a particle to move it to a new position.**

## 5.6. Fitness Function:

Equation 5.4 is used to quantize the quality of the solution represented by each particle of the swarm in terms of their fitness value.

Cost(x) = APL + ϑ Equation (5.3)

F(x) = 1 / Cost(x) Equation (5.4)

Where,

APL = Average Path Length

ϑ = Number of 'directed edge disjoint route' sets.

‘$\vartheta$’, here is equivalent to the number of wavelengths required to set up given lightpath requests, using routes in the current particle. All the routes in each of these ‘directed edge disjoint route’ set can be assigned same wavelength, as no two routes in a single set can share a common directed edge of the network and therefore don’t violate ‘wavelength clash constraint’. However each set needs to be assigned a distinct (unique) wavelength. This also removes the need to have a separate ‘wavelength assignment’ algorithm, for calculating appropriate wavelength for each route.

## 5.7. Calculating the number of edge disjoint route sets:

For each particle, the number of ‘edge disjoint route’ sets resulted because of route selection in the current particle can be calculated as:

- Create an empty set of disjoint routes and sort all the routes in the particle in decreasing order of their path length in terms of number of hops.
- Pick up a route, and insert it in the set such that no two routes with a common edge should lie in the same set.
- If route cannot be placed in all the previous sets, create a new set and place the route there.

## 5.8. Pseudo Code for the Proposed PSO-based static RWA (PSO-lb) Algorithm:

The pseudo code for the PSO-lb algorithm used to solve static RWA problem, when a set of connection requests are given.

- Initialization (for each particle):
    - o Randomly select a route (from pre-computed K-shortest paths) for each connection request, and assign it to the particle.
    - o Apply fitness function to quantize the particle in terms of its fitness value.
    - o Mark the particle having best fitness value in the whole swarm as Global best.
    - o Mark the best particle in the local neighbourhood (sub-swarm) as Local best.

- For each particle Do:
    - Find the velocity for the particle according to Global best or local best particle. This will give the ‘y’ number of routes in current particle that needs to be replaced in the current particle by routes from Global best or local best particle.
    - Consult the ‘common edge usage table’ of the particle, and select ‘n’ routes which are different in both the particles and traverse through the most congested edges on the network (Only St (1) is used here)
    - Replace those routes in the current particle with the corresponding routes in the Global best or local best particle.
- At the end of each iteration, re-apply the fitness function to update the Global/Local best particles.
- Iterate for a pre-defined number of iterations.

## 5.9. Proposed Novel Strategies to Improve Problem Space Search:

In PSO, a new velocity needs to be computed for each particle in the swarm. This velocity will then move the particle from the current position to some other position in the problem search space. In the proposed PSO-lb scheme for static RWA, one way to compute velocity for a particle can be done simply by randomly choosing routes from the vector ‘$P_1$-$P_2$’ (Shown in figure 5.2 (b)) into the velocity vector. Another way can be the route-id selection according to some criteria that can help improve the search capability of the swarm. In order to help the particles find a combination of routes that can move them to a position with better fitness value, a strategy called *St. (1)* here, has been proposed. This scheme helps to prioritize the replacement of routes within in a particle. To help the particles to move towards a better position quickly, while avoiding local minima as much as possible, a strategy called *St. (2)* has been proposed.

At the same time, to diversify the problem space search, a novel operation has been proposed for global best particle, in *St. (3)*. This operation attempts to improve the fitness value of global best particle. Unlike traditional particle swarm optimization, S*t. (3)* causes the global best particle to explore the problem search space. However, the advantage of this operation is that the global best particle will always move to a better position, i.e. towards the best position within its locality.

- *St. (1)*: For the current particle, select those routes which traverse the most congested edges of the network. The edge usage table associated with the particle can help to determine this.
- *St. (2)*: Instead of randomly selecting the routes over the most congested edges to be replaced by routes in global/local best particle, replace a route in the current particle with an alternate route (from global/local best) 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.
- *St.* (3): Only for global best particle in the swarm, 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. (‘t’ is an algorithmic parameter)

## 5.10. Simulation Results and Analysis:

A simulator has been developed in Opnet™ in order to implement the proposed PSO-lb scheme for static RWA algorithm in windows environment. 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 [103].

### 5.10.1. Theoretical Lower Bounds ($LB_W$ *and* $LB_{APL}$)

In order to determine the performance of the proposed algorithm, a lower bound for the number of wavelengths required is used as presented in [104]. The bound on the number of wavelengths needed to establish a given set ‘T’ of ‘n’ lightpath requests in a network ‘G’ with |V| nodes and |Ep| edges can be calculated by (5.4), as follows

$$LB_W = \max\left\{ \max_{i \in V} \left\lceil \frac{\Delta_l(i)}{\Delta_p(i)} \right\rceil, \left\lceil \frac{\sum_{j=1}^{n} l(SP_j)}{2 * |E_p|} \right\rceil \right\}$$

Equation (5.4)

$\Delta_l$ *(i)* represents the logical degree of node *i*, i.e. the number of lightpaths for which node *i* is the source node. $\Delta_p$ *(i)* represents the physical degree of node *i*. $l(SP_j)$ is the length of the shortest path in G of lightpath request ($s_j$,$d_j$), where '$s_j$' is the source node and '$d_j$' is the destination node.

For the experiments, a uniform traffic demand is assumed. Then, if $l(SP_j)$ is the length of the shortest path in 'G' of lightpath request ($s_j$,$d_j$), and $|V|$ is the number of nodes in the network, then the lower bound for the average path length can be calculated by (5.5), as follows:

$$LB_{APL} = \frac{\sum_{j=1}^{|n|} l(SP_j)}{|V| \times \left(|V| - 1\right)} \qquad \text{Equation (5.5)}$$

These lower bounds given by eq. 5.4 and eq. 5.5 are theoretical bounds and may not be achievable practically.

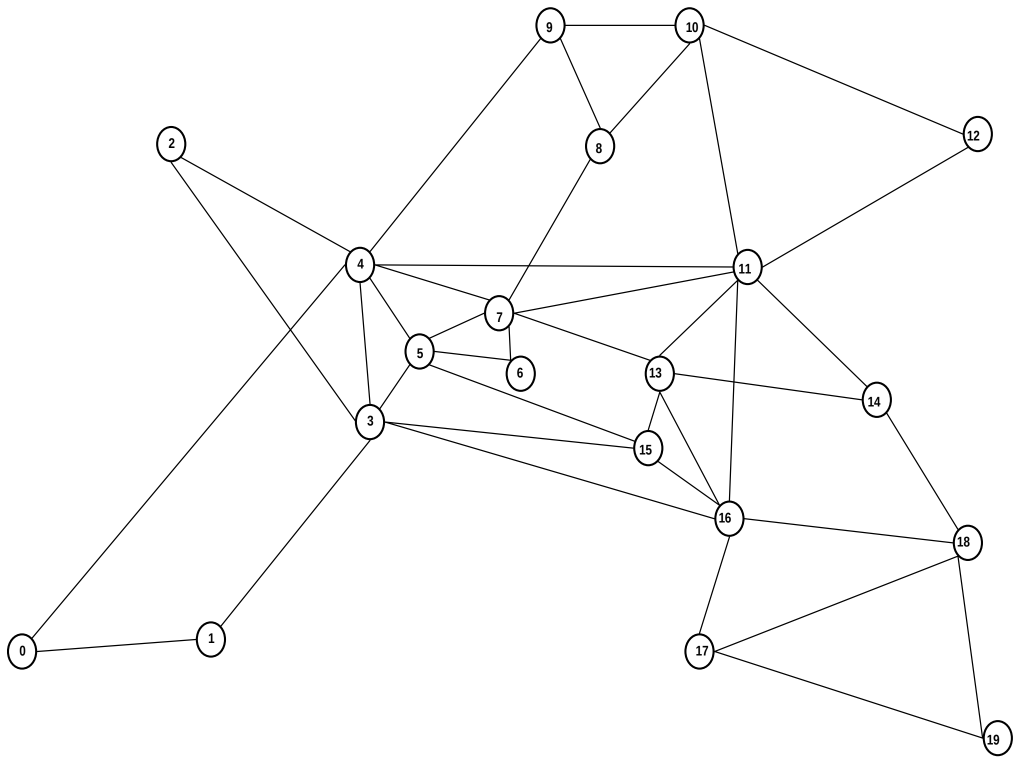


**Figure 5.4: 20 Nodes, 39 Edges EON Network**

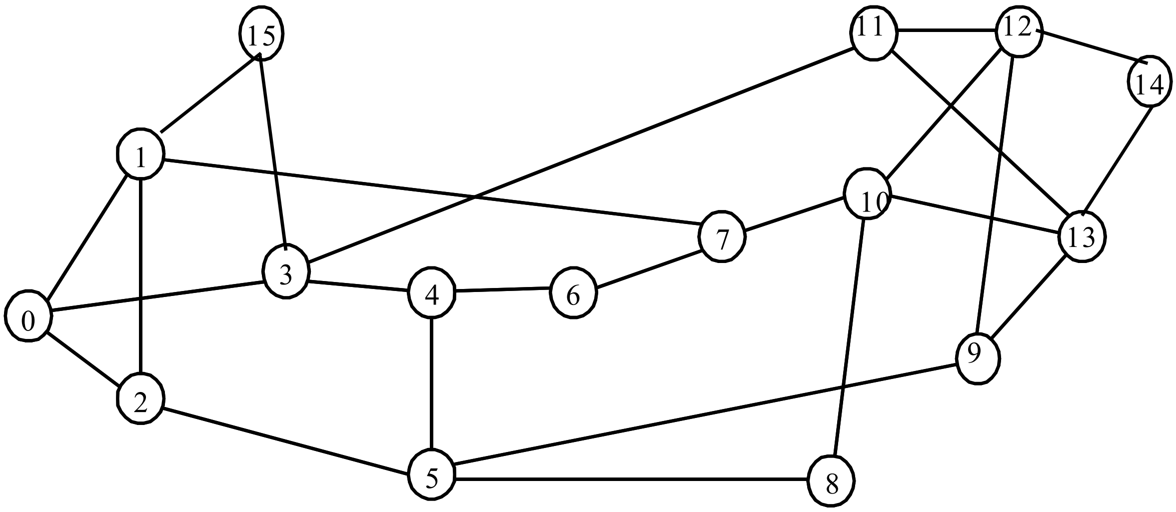


**Figure 5.5: 16 Nodes, 25 Edges NSFNET Network**

A set of simulations have been done using proposed PSO-lb algorithm for the networks shown in figures 4.2, 5.4 and 5.5. For each network, the simulation is repeated 15 times using different seed values and the average values are reported.

## 5.10.2. Performance Comparison with other Heuristic Schemes:

For any static RWA algorithm, a fundamental objective is to minimize the number of wavelengths required to provision a given set of connection requests. Another desirable feature is to minimize the average path length of the chosen routes. Minimizing average path length help to conserve network resources used to provision connection requests.

Table 5.1 illustrates the performance of PSO-lb algorithm used to solve static RWA problem, when a set of connection requests are given. All three strategies, St. (1), St. (2) & St. (3) are used. The achieved performance of PSO-lb in terms of number of wavelengths required ($\vartheta$) and average path length (APL) is compared against the $LB_W$ (Lower bound on the number of wavelength required), $LB_{APL}$ (Lower bound on the average path length). $LB_W$ and $LB_{APL}$ are theoretical lower bounds and might not be achievable practically. The given set of connection requests contains a lightpath request between every source-destination pair in the network. The total number of requests in the given set contains N*(N-1) number of connection requests where 'N' is the number of nodes in the network. For example: In the case of the 14-node NSFNET (figure 4.2), the set of connection requests contain 14*13=182 connection requests. The simulation results show that the proposed scheme can achieve optimal/near-optimal solution for a given set of connection requests. This can be verified by comparing the results achieved by PSO-lb with respect to the lower bounds on '*minimum number of wavelengths required*' and '*average path lengths of the chosen routes*' represented by equation 5.4 and 5.5 respectively. Here, swarm convergence is defined as the number of iterations required by the swarm to converge at a single position (a candidate solution) in the problem search space.

**Table 5.1: Experimental results of PSO-lb for static RWA for networks showed in the figure 4.2 and 5.4. NS = Neighbourhood size, Social learning parameter ($C_1$, $C_2$), No. of KSP = Number of K-Shortest paths considered for each possible source-destination pair, APL = average path length achieved, $\vartheta$ = Number of edge disjoint route sets i.e. number of wavelengths required to provision all given set of connection requests.**

| | Swarm Size | NS | Social Learning Parameter | No of GB Re-attempts 't' | No. of KSP | Swarm Convergence | APL | $\vartheta$ |
|---|---|---|---|---|---|---|---|---|
| **NSFNET (Figure 4.2) $LB_W = 13$ $LB_{APL} = 2.14$** | 14 | 3 | C1 = 0.05<br>C2 = 0.05 | 4 | 2 | 1369.3 | 2.3626 | 13 |
| **EON (Figure 5.4) $LB_W = 18$ $LB_{APL} = 2.36$** | 18 | 3 | C1 = 0.05<br>C2 = 0.05 | 4 | 3 | 2917.4 | 2.744 | 18.2 |

The results in table 5.1, show clearly that the proposed PSO-lb algorithm achieves the lower bound on the number of wavelengths required while minimizing the average path length (APL) as identified in [105], in significantly fewer iterations. For example, in the case on 14-node NSFNET, [105] achieves $LB_W$ = 13, in 9299 iterations with average path length of 2.5400. On the other hand, the proposed algorithm achieves $LB_W$ = 13, in just 1369 (approx.) iterations with an average path length of 2.3626 in order to setup 182 lightpath requests. So there is a significant improvement both in terms of number of iterations required and average path length, while reaching $LB_W$ = 13, for 14-node NSFNET. Similarly, as compared to a genetic algorithm proposed in [94], which requires 23 wavelengths to set up 100 SD pairs (source- destination pair) in 14-node NSFNET, the proposed algorithm can set up 182 SD pairs in just 13 wavelengths (First-Fit algorithm requires 41 wavelength to set up 100 SD pairs in NSFNET [94]).

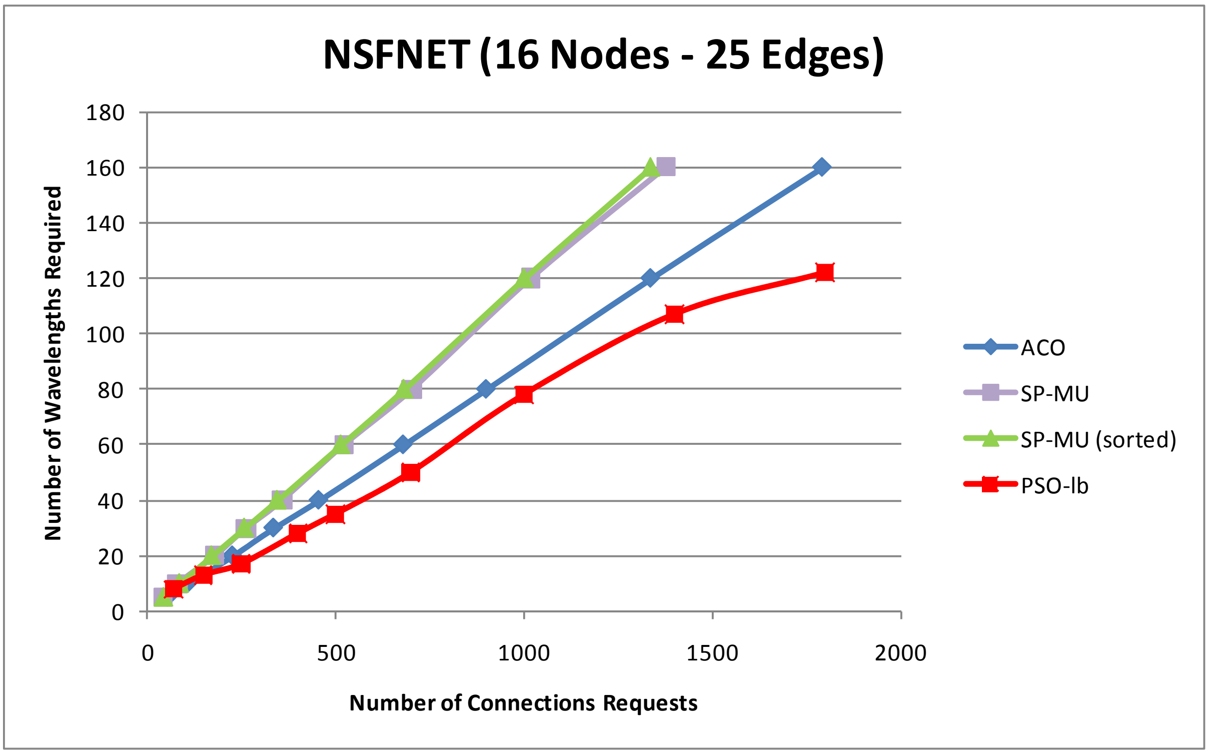


**Figure 5.6: Performance Comparison between the proposed PSO-lb, ACO [96], SP-MU and SP-MU (sorted) in terms of number of wavelengths required in-order to set-up a given set of connection requests in 16-node NSFNET (figure 5.5). For PSO-lb, Number of particles used = 16, NS = 3, KSP = 5, Number of GB re-attempt't' = 4, $C_1 = C_2 = 0.05$, Maximum number of iterations allowed = 3500.**

Ant Colony Optimization is another swarm intelligence scheme inspired by the behaviour of colony of ants where multiple agents (ants) explore the solution space biased by the pheromones laid by other ants. An implementation of ACO meta-heuristic framework is used in [96] to solve static RWA problem. In figure 5.6, a performance comparison is done between the proposed PSO-lb algorithm, ACO [96] algorithm, Shortest-Path with Most-Used wavelength assignment algorithm (SP-MU) and Shortest-Path + Most-Used algorithm with connection requests sorted according to the hop-length (SP-MU sorted). In this case, a set of connection requests is generated between randomly selected source-destination node pair for 16-node NSFNET (figure 5.5). The source and destination nodes are chosen randomly with uniform distribution and the number of wavelengths required to setup all the connection requests in the given set is computed. Figure 5.6 shows that the proposed PSO-lb scheme performs significantly better as compared to ACO, SP-MU and SP-MU (sorted) algorithms used to solve static-RWA.

The main reason of better performance in case of proposed PSO-lb scheme is the use of proposed novel strategies (St. (1), St. (2) and St. (3)). These strategies not only enable the particles to choose routes leading to better fitness values. They also help the particles to avoid locally optimal solutions (particularly St. (3)).

### 5.10.3. Effect of St. (1), St. (2) and St. (3) on the performance of PSO-lb

The proposed novel strategies St. (1) and St. (2) when used with PSO-lb, prioritize the selection of route-ids for inclusion in the new velocity of the particle. The routes (uniquely identified by route-id), which traverse most congested edges of the network, are given preference for replacement. These chosen routes will consequently be replaced with the respective routes of some other particle having better fitness values i.e. either local best particle of the neighbourhood or global best particle of the whole swarm. As a result of that, there's a better chance that the current particle will be successful in acquiring some route (learning from the position of local-best or global-best particle) which will help to reduce the congestion (in terms of number of routes traversing) on the edges. Congestion over an edge can be evaluated by inquiring the associated edge usage table of that respective particle. Since each route traversing an edge needs to be assigned a unique wavelength in order to satisfy '*wavelength clash* constraint', therefore reducing congestion on an edge indirectly also reduces the number of the wavelengths required to set-up given set of connection requests. In other words, *St. (1)* indirectly decreases the number of wavelengths required and average path length, by replacing routes traversing the most congested edges of the network.

St. (3) tries to reinitialize the solution represented by its position such that the re-initialization can lead the global-best particle to some position having better fitness value. This also helps the global-best particle in the swarm to avoid being stuck in local optimal solution by diversifying the problem search by giving an opportunity to fine tune and improve its position towards better fitness value. The movement of all other particles in the swarm is influenced by the position of global best particle. Therefore, to some extent it also helps the swarm to avoid premature convergence.

Table 5.2 and table 5.3 summarize the comparative results of using different combinations of proposed strategies route-id selection during velocity computation, for the 14-node NSFNET (figure 4.2) and EON (figure 5.4). In order to increase the size of problem search space, the number of pre-computed K-Shortest paths (KSP) is increased to 8 in each case. N*(N-1) number of connection requests are considered, where 'N' = number of nodes in the network. Each experiment is repeated 15 times and the averages are reported here. The results show that *St. (1)* and *St. (3)* significantly improve the results both in terms of wavelengths and APL. *St. (2)* shows slight improvement in terms of swarm convergence but not as significantly as *St. (1)* and *St. (3)* do alone.

**Table 5.2: Experimental results of PSO-lb algorithm for static RWA, using different combinations of proposed strategies, St. (1), St. (2) and St. (3) under same network conditions for 14-Node NSFNET. KSP = 8, Number of particles = 14, C1=C2=0.05, Neighbourhood size = 3.**

| | Strategy Used | Maximum Iterations | Iteration Number of Last Improvement | Swarm Convergence | APL | $\vartheta$ |
|---|---|---|---|---|---|---|
| NSFNET (Figure 4.2) $LB_W$ = 13 $LB_{APL}$ = 2.14 | None | 3000 | 1435.2 | 1547.2 | 3.748 | 27.4 |
| | St (1) | 3000 | 1660.2 | 1788.2 | 3.415 | 18.93 |
| | St (1) and St (2) | 3000 | 1639.8 | 1823.6 | 3.357 | 17.93 |
| | St (1) and St(3) | 3000 | 2498.33 | 2603.786 | 2.630 | 14.26 |
| | St (1) , St (2) and St (3) | 3000 | 2329.33 | 2513.33 | 2.676 | 14.257 |

The same pattern of performance in terms of number of wavelengths required and average path length of the chosen routes can be seen in the case of EON (table 5.3), when different combinations of proposed strategies for route-id selection in velocity computation are used along with PSO-lb algorithm.

**Table 5.3: Experimental results of PSO-lb algorithm for static RWA, using different combinations of proposed strategies, St. (1), St. (2) and St. (3) under same network conditions for EON. KSP = 8, Number of particles = 18, C1=C2=0.05, Neighbourhood size=3.**

| | Strategy Used | Maximum Iterations | Iteration Number of Last Improvement | Swarm Convergence | APL | ϑ |
|---|---|---|---|---|---|---|
| EON (Figure 5.4) $LB_W = 18$ $LB_{APL} = 2.36$ | None | 5000 | 2619.6 | 2738.8 | 3.210 | 28 |
| | St (1) | 5000 | 2756.73 | 2904.86 | 3.122 | 19.73 |
| | St (1) and St (2) | 5000 | 2702.66 | 2968.73 | 3.092 | 19.53 |
| | St (1) and St(3) | 5000 | 3604.9 | 4000.7 | 2.953 | 19 |
| | St (1) , St (2) and St (3) | 5000 | 3280.8 | 3806.76 | 2.971 | 18.8 |

## 5.10.4. Effect of Maximum number of Iterations allowed on performance of PSO-lb:

In some situations especially in dynamic environments a solution of reasonable quality is desirable within a specified time scale. One way to achieve this in the case of evolutionary algorithms e.g. swarm intelligence algorithms, is to allow the algorithm to evolve for a specific number of iterations. In the case of PSO, this can easily be achieved by allowing the swarm to evolve for a given number of iterations while saving the position of global-best particle in the swarm (searched so far). If the swarm converges within that given number of iterations or if the maximum allowed iterations is reached, this value will give the best solution searched by PSO.

Table 5.4 summarizes the effect of variable number of 'maximum allowed iterations' on the performance of PSO-lb. It is clear from the results that up to a certain number of iterations, the fitness value or the global-best solution quality improves as the number of 'maximum iterations allowed' is increased. However, after that the solution quality doesn't improve much. For example: In case of EON, when the swarm was allowed to evolve for a maximum of 3000 iterations, the last iteration where improvement in the fitness value is observed is

2770 (approx) which is close to the maximum allowed iterations. However, when the number of maximum allowed iterations is increased to 5000, the last iteration number showing improvement in the fitness value is just 3280 (approx) which is far from the maximum iterations allowed.

**Table 5.4: Experimental results of PSO-lb algorithm for static RWA for 14-node NSFNET (figure 4.2) and EON (figure 5.4) with variable 'maximum number of iterations allowed'. All three strategies for route-id selection (St (1), St (2) and St (3) are used. KSP = 8.**

| | Swarm Size | NS | Social Learning Parameter | No of GB Re-attempts 't' | Max Allowed Iterations | Iteration # of Last Improvement | APL | ϑ |
|---|---|---|---|---|---|---|---|---|
| **NSFNET (Figure 4.2)** $LB_W = 13$ $LB_{APL} = 2.14$ | 14 | 3 | C1 = 0.05 C2 = 0.05 | 4 | 200 | 186.2 | 3.924 | 23.4 |
| | | | | | 500 | 476.8 | 3.443 | 19.8 |
| | | | | | 1000 | 969.2 | 3.090 | 17.07 |
| | | | | | 1500 | 1469.3 | 2.875 | 15.47 |
| | | | | | 2000 | 1915 | 2.805 | 14.74 |
| | | | | | 3000 | 2329.33 | 2.676 | 14.26 |
| **EON (Figure 5.4)** $LB_W = 18$ $LB_{APL} = 2.36$ | 18 | 3 | C1 = 0.05 C2 = 0.05 | 4 | 200 | 191.33 | 3.413 | 25.33 |
| | | | | | 500 | 471.923 | 3.287 | 22.84 |
| | | | | | 1000 | 969.26 | 3.162 | 20.93 |
| | | | | | 2000 | 1919.2 | 3.052 | 19.46 |
| | | | | | 3000 | 2772.12 | 2.984 | 19 |
| | | | | | 5000 | 3280.2 | 2.971 | 18.8 |

## 5.10.5. Neighbourhood Size:

The neighbourhood for a particle is defined as a sub-collection of particles in the swarm that influence its movement in the problem search space being addressed. In other words, a group of particles which are within a certain distance from a particular particle in the problem search space, where distance between two particles can be defined as the difference between the fitness values of these two. In PSO-lb, distance is defined in terms of degree of similarity in the number of routes between two particles.

Eberhart and Kennedy in [61] concluded that smaller local neighbourhoods helps the particles to avoid local minima and that a global neighbourhood (where all other particles in the swarm are considered to be part of the particle's neighbourhood) help the particles to converge faster. In [106], the neighbourhood size is increased from small local neighbourhoods ultimately up to a global topology. In this case, increasing the neighbourhood size resulted in encouraging, yet ultimately inconclusive results [107].

Figure 5.7 shows simulation results PSO-lb performance in terms of fitness value of the global-best particle. The EON network, shown in figure 5.4, is considered where the number of connection requests is 380 (One lightpath request from every source to every possible destination in the network) and the each simulation is carried out 15 times for different seed values and the averages are plotted in the graphs. With PSO-lb, all three strategies proposed in section 5.9 are used. The results shows that changing the neighbourhood size from small sized neighbourhood to large local neighbourhood doesn't have significant affect the performance of PSO-lb in terms fitness values and the average path length of the chosen routes. The main reason is that the proposed strategies St (1), St (2) and St (3) always guide the particles in the swarm to select particular routes leading to more or less same fitness values. The strategies also avoid those routes that have the potential to deteriorate the fitness values of the particles in the swarm, irrespective of the size of the local neighbourhood.

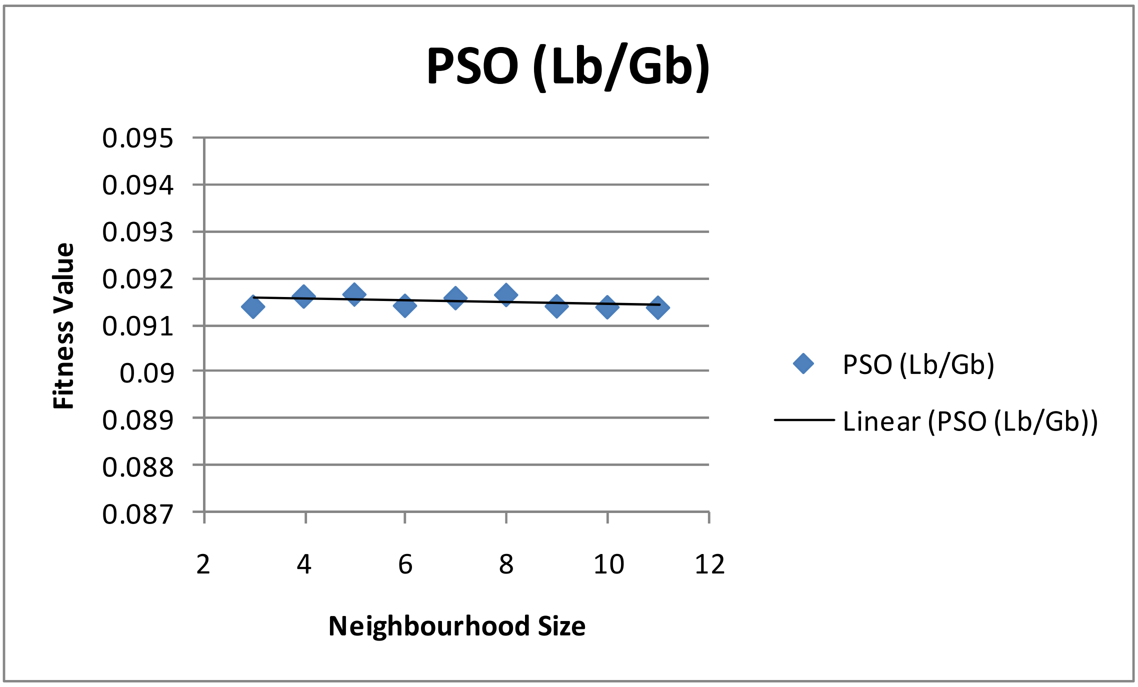


**Figure 5.7: PSO-lb performance in terms of Fitness Value VS Variable Neighbourhood size for EON (figure 5.4). Maximum number of iterations allowed = 5000, KSP = 8, Number of particles = 18. Number of GB re-attempt't' = 4, $C_1 = C_2 =$ 0.05.**

### 5.10.6. Social Learning Parameters ($C_1$, $C_2$)

During the velocity computation of the particle, social learning parameters in PSO decide the amount of influence of the position of local-best particle and global-best particle in the swarm. In PSO-lb, they determine how many routes in the current particle should be considered for replacement with the respective routes in local-best or global-best particle. In a single iteration of PSO-lb, each particle will adjust its position according to the position of local-best particle or global-best particle; but not both at the same time.

In order to examine the effect of different values of social learning parameter on the performance of PSO-lb, a set of simulations is carried out for 14-node variant of NSFNET. Only the strategy St (1) is used with PSO-lb algorithm. Each experiment is carried out 15 times and the average is plotted in the figure 5.8, 5.9 and 5.10.

Figure 5.8 clearly shows that as the value of C1 (when the particle is influenced by the position of local-best particle) or C2 (when the particle is influenced by the position of global-best particle) is increased, the fitness value of the function deteriorates. The reason for this is evident from figure 5.9 and 5.10, which clearly shows that increasing the value of social learning parameter results in rapid (or pre-mature) convergence of the swarm particles. This pre-mature convergence hinders the particles to search the problem space properly and therefore depreciate the fitness value of the particles.

Lower values of social learning parameter limits the influence of the positions of local-best or global-best particles during the velocity computation of the particle and help in avoiding pre-mature convergence. This ultimately leads to improvement in the solution quality being represented by the fitness values of the swarm. At the same time, decreasing social learning parameter values for particles in the swarm during velocity computation result in increase in the number of iterations required for the swarm to converge. Subsequently, this increases the computational time complexity of the static RWA algorithm. Therefore, there is a trade-off between the swarm convergence (computational time) and fitness values.

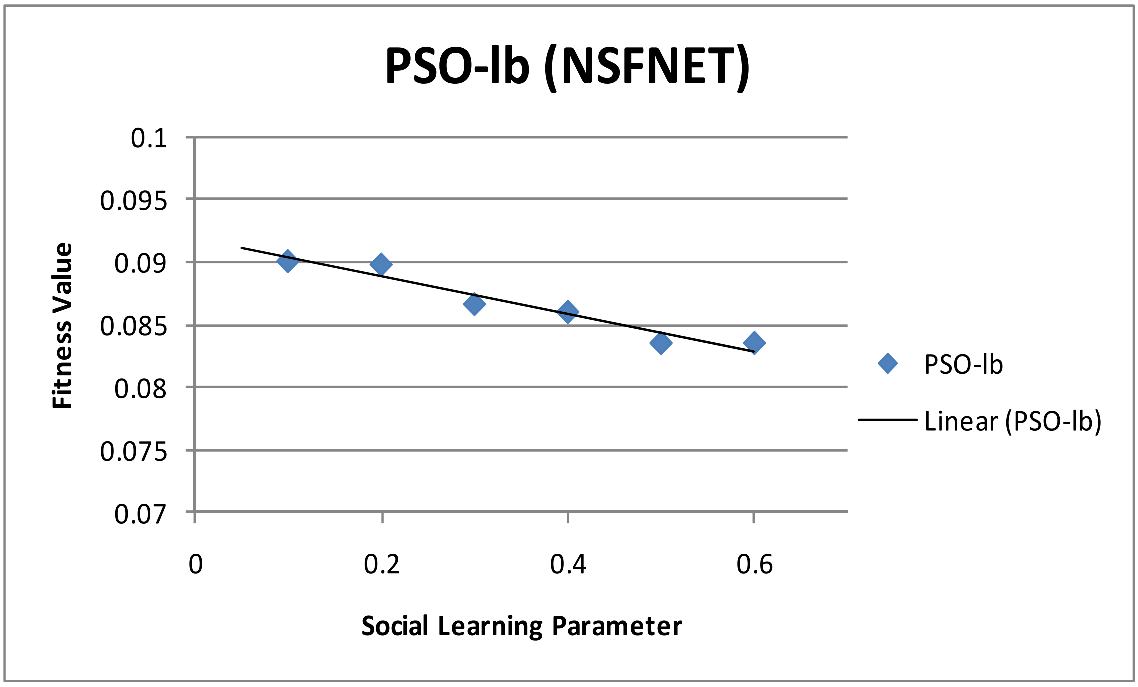


**Figure 5.8: PSO-lb performance in terms of Fitness Value for Variable Social Learning Parameter for NSFNET (figure 4.2). Maximum number of iterations allowed = 3500, KSP = 8, Number of particles = 14.**

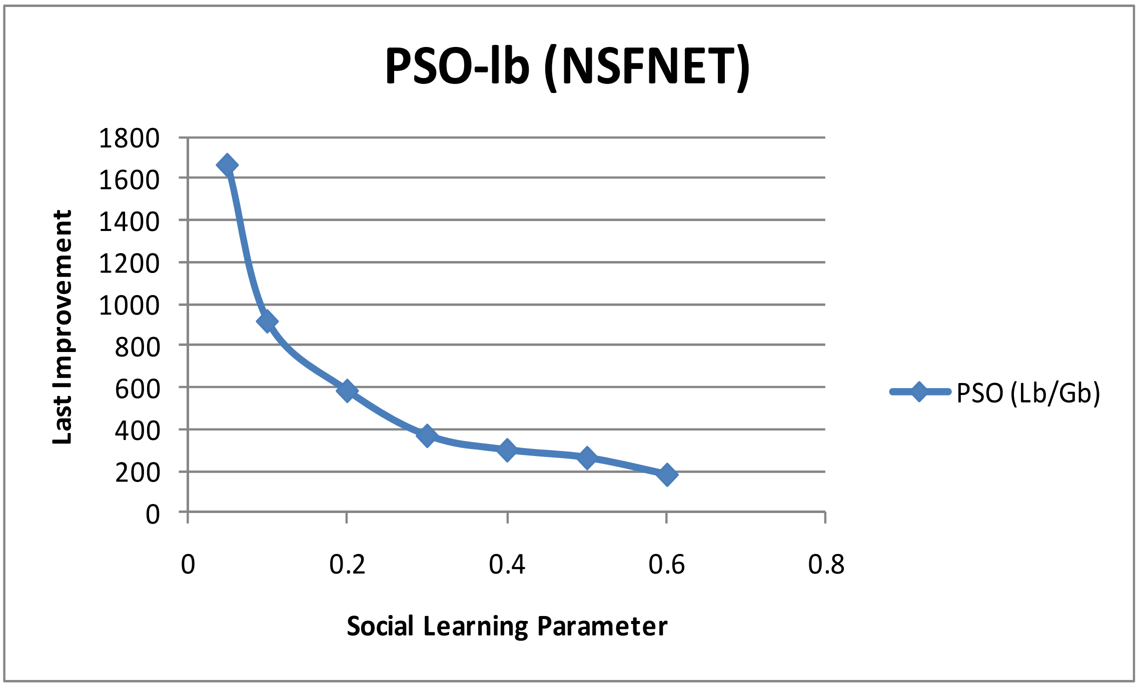


**Figure 5.9: PSO-lb performance in terms of Last Improvement in the fitness value for Variable Social Learning Parameter for NSFNET (figure 4.2). Maximum number of iterations allowed = 3500, KSP = 8, Number of particles = 14.**

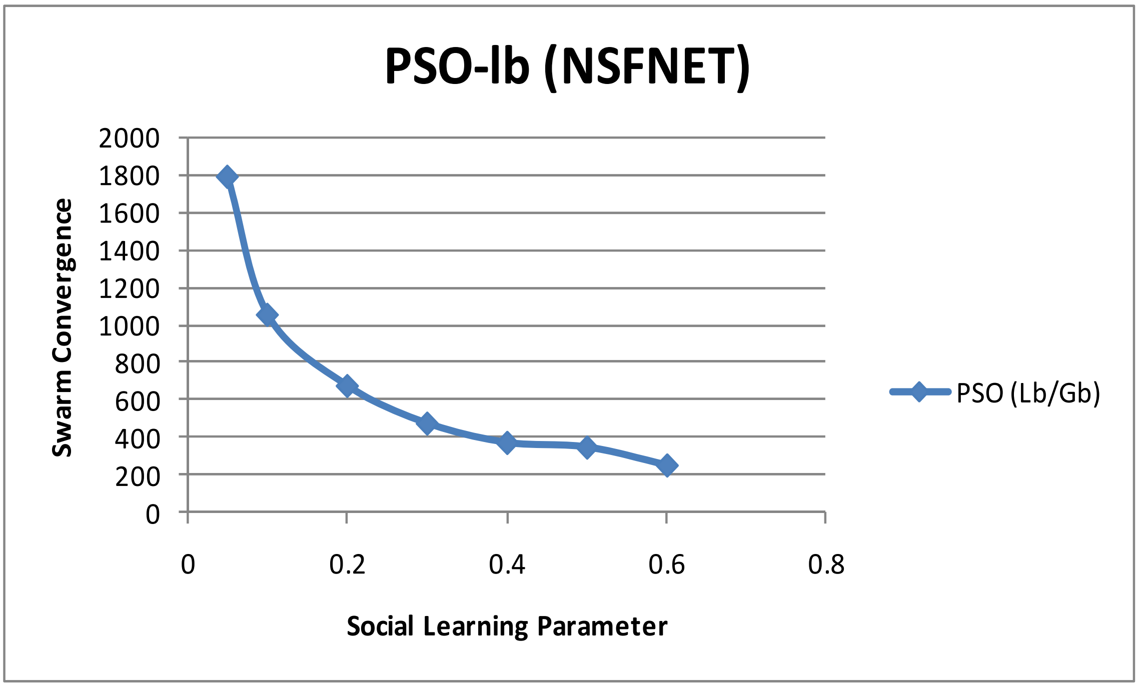


**Figure 5.10: PSO-lb performance in terms of Swarm Convergence for Variable Social Learning Parameter for NSFNET (figure 4.2). Maximum number of iterations allowed = 3500, KSP = 8, Number of particles = 14.**

### 5.10.7. Number of pre-computed K-Shortest paths (KSPs):

In the proposed PSO-lb algorithm to solve static RWA problem, the particles are encoded such a way that the position of a particle is represented by a vector of route-ids. Each route-id uniquely identifies a route with in the pre-computed set of K-shortest path between a specific source-destination pair. In PSO-lb, 'k' number of pre-computed paths between every possible source-destination pair in the network is considered. Increasing the number of these pre-computed K-Shortest Paths (KSPs) increases the problem search space for the particle.

In order to evaluate the effect of different number of KSPs on the performance of PSO-lb, a set of simulations are undertaken for the 14-node NSFNET (figure 4.2) and EON (figure 5.4). Each simulation is carried out 15 times using different seeds for random number generator and the average is plotted here. The total number of connection requests given = N * (N-1) where 'N' is the number of nodes in the network.

Figure 5.11 shows that as the number of KSPs increases, the number of wavelengths required to setup given set of connection requests increases slightly. Similarly, figure 5.12 shows that with the increase in the number of pre-computed KSPs, the average path length (APL) of the chosen routes increases. The reason is increasing KSP, increases the problem search space for the particle to search. With this increase, the swarm particles now have to search for optimal solution among more possibilities (or position points). The optimal solution here actually is the best selection of routes for the given set of connection requests such that their unique combination followed by wavelength assignment leads to minimal number of wavelengths required and minimal average path length at the same time.

Since increasing pre-computed KSPs results in an increased number of wavelengths required and increased APL, this ultimately results in a decrease in the fitness value of the best solution represented by global-best particle as shown in figure 5.13. However, it is equally important to have a sufficient number of KSP to find a combination of routes leading to the best solution in terms of quality. This can be clearly seen in figure 5.13 in the case of EON, which is a relatively large network as compared to NSFNET. Therefore, in the case of EON, considering 3 KSPs results in a better fitness value as compared to when just 2 KSPs are considered.

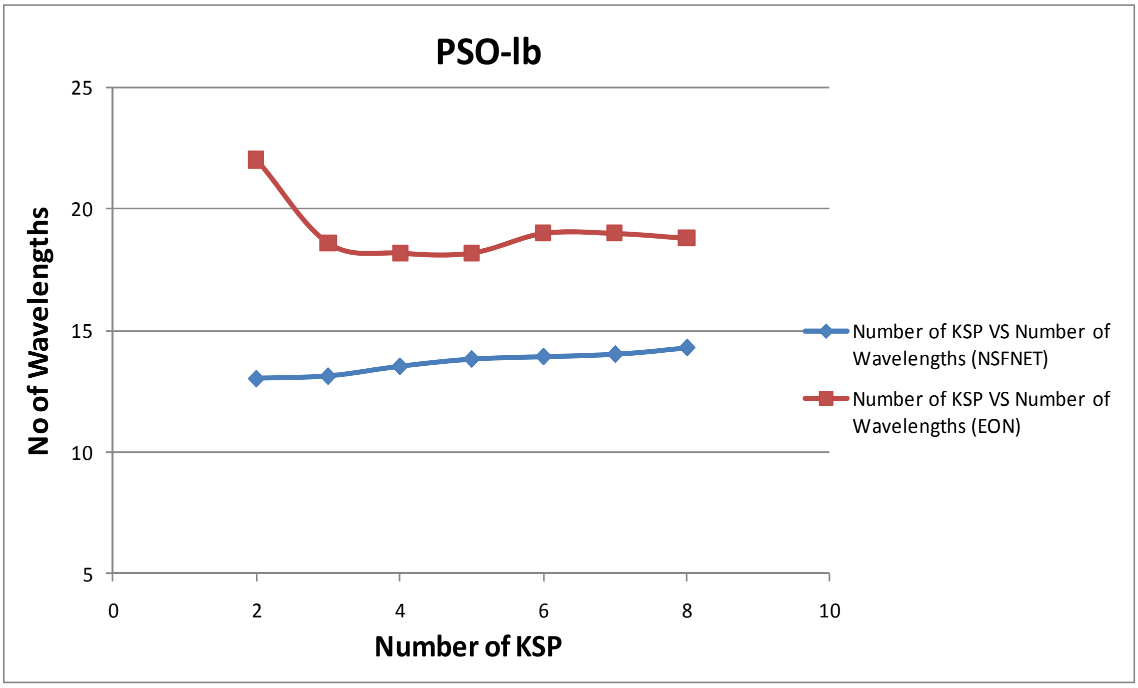


**Figure 5.11: PSO-lb performance for different number of KSP in terms of number of wavelengths required. Maximum number of iterations allowed = 3500 (NSFNET) and 5000(EON), C1 = C2 = 0.05, Number of particles = 14 (NSFNET) and 18 (EON).**

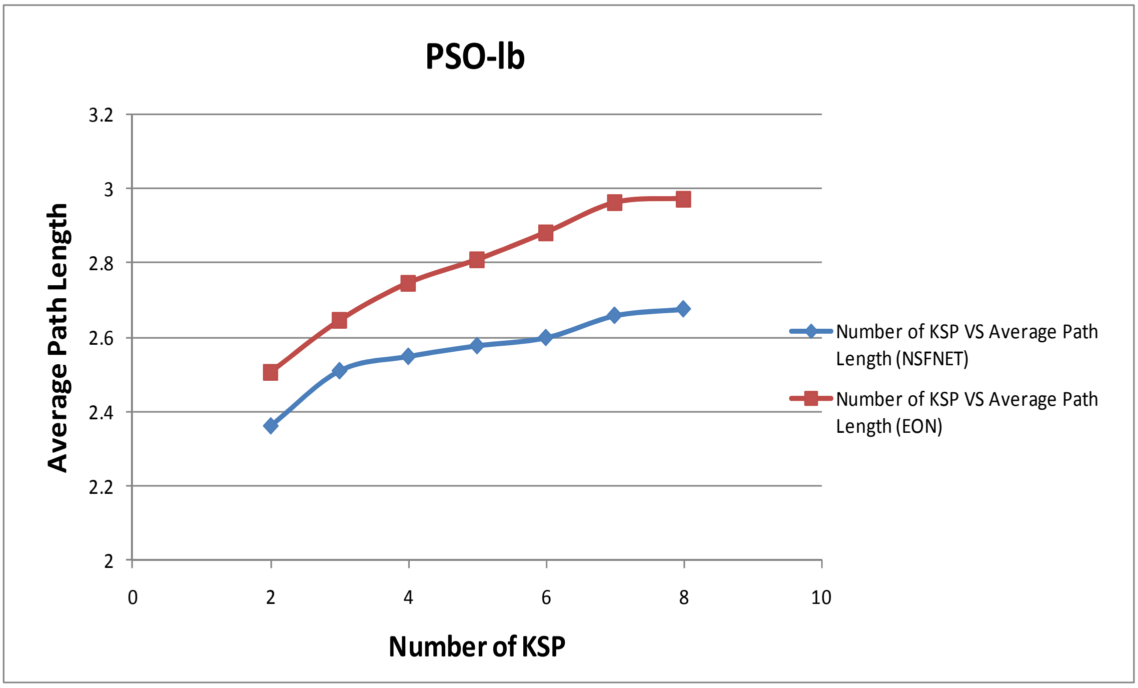


**Figure 5.12: PSO-lb performance for different number of KSP in terms of average path length of the chosen routes. Maximum number of iterations allowed = 3500 (NSFNET) and 5000 (EON), C1 = C2 = 0.05, Number of particles = 14 (NSFNET) and 18 (EON).**

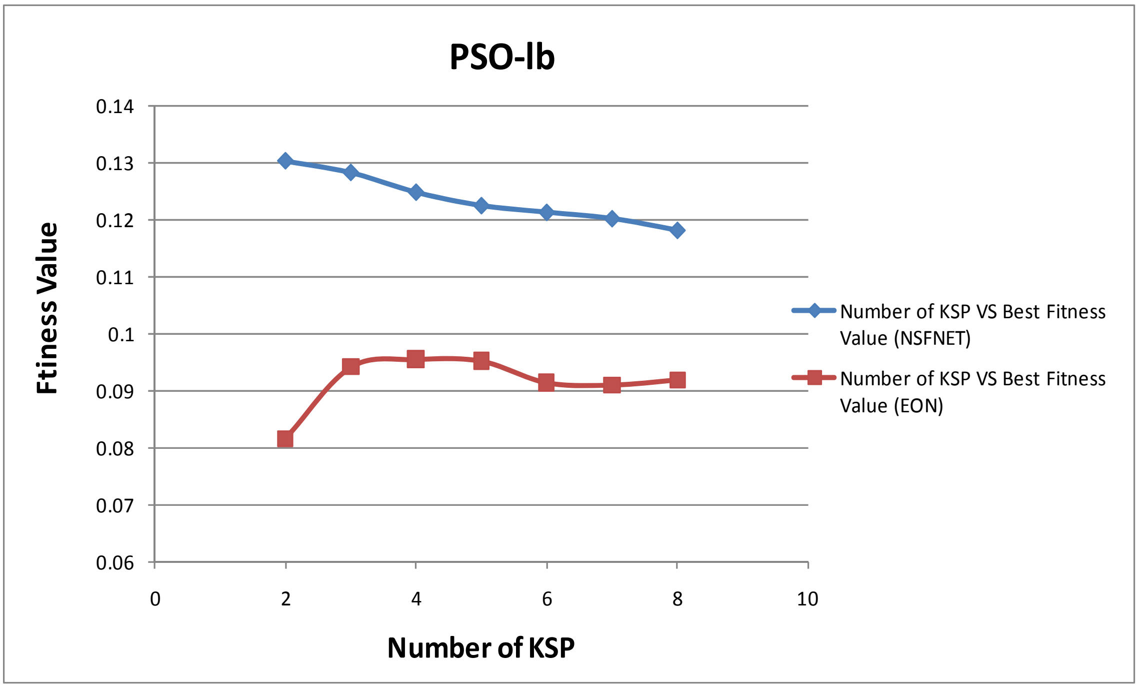


**Figure 5.13: PSO-lb performance for different number of KSP in terms of fitness value. Maximum number of iterations allowed = 3500 (NSFNET) and 5000 (EON), C1 = C2 = 0.05, Number of particles = 14 (NSFNET) and 18 (EON).**

Figure 5.14 and figure 5.15 clearly show that with increasing number of KSPs, the number of iterations for the last improvement in the fitness value and the swarm convergence (i.e. number of iterations required by the swarm to converge) increases too. The main reason for this trend is an increase in the problem search space which the particles now have to search. Therefore, particles take more iterations to converge at a solution when the number of KSPs considered increases.

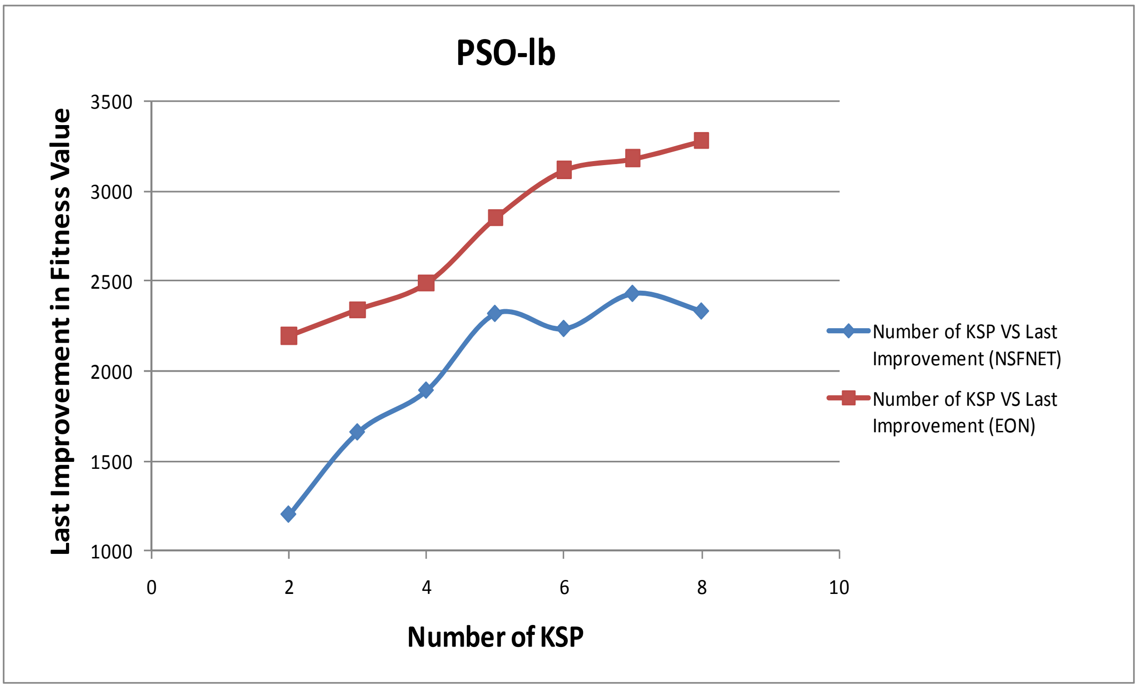


**Figure 5.14: PSO-lb performance for different number of KSP in terms of Last Improvement in the fitness value. Maximum number of iterations allowed = 3500 (NSFNET) and 5000 (EON), C1 = C2 = 0.05, Number of particles = 14 (NSFNET) and 18 (EON).**

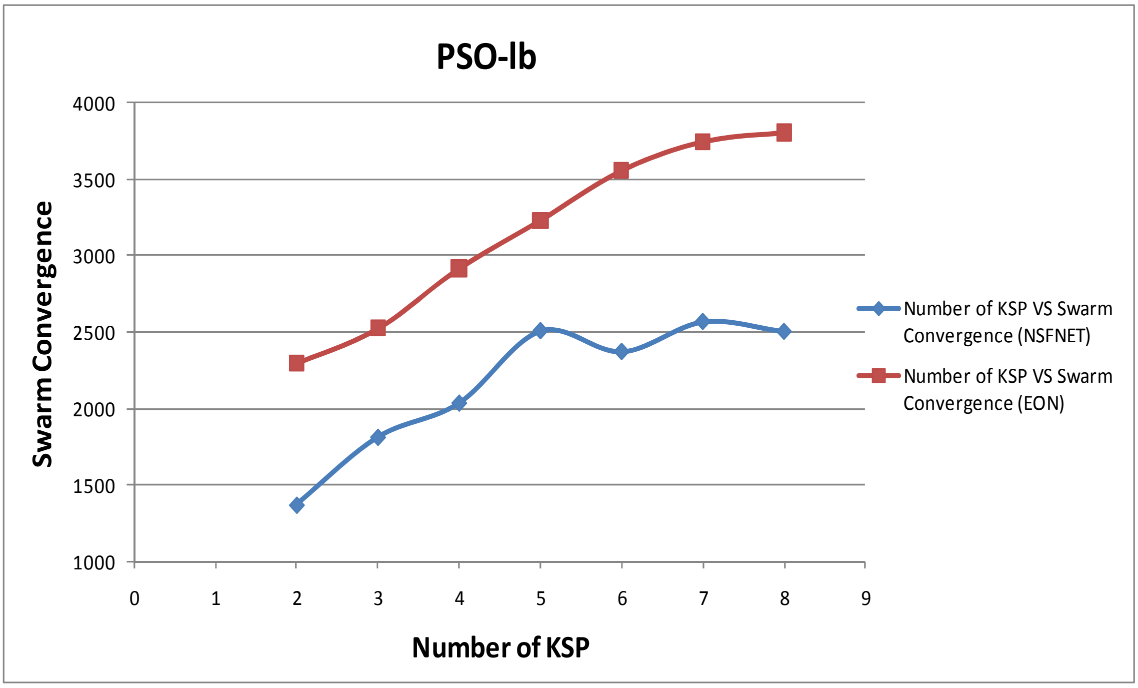


**Figure 5.15: PSO-lb performance for different number of KSP in terms of Swarm Convergence. Maximum number of iterations allowed = 3500 (NSFNET) and 5000 (EON), C1 = C2 = 0.05, Number of particles = 14 (NSFNET) and 18 (EON).**

### 5.10.8. Number of Re-Attempts for Global-best particle in St (3):

St (3) only operates on the global best particle in the swarm. It tries to replace a route (represented by route-id in its position vector) with an alternative route from the pre-computed set of k-shortest paths. In a single re-attempt, if an alternative route is found such that congestion on the most loaded link in the alternative is lower than the congestion of the most loaded link in the previously assigned route, the current route is replaced. In order to evaluate the effect of number of such route replacement attempts (referred to as re-attempts here), a set of simulations are carried out for the 14-node variant of NSFNET (figure 4.2).

As shown in figure 5.16, as the number of re-attempts is increased from 1 till 6, the fitness value of the particles improves. The reason is that when there is a successful re-attempt of route replacement, the congestion of the most loaded link in the old route is decreased. This indirectly attempts to reduce the lower limit on the number of wavelengths required (shown in figure 5.17) and Average Path Lengths of the chosen routes (shown in figure 5.18), which results in improvement in the fitness value.

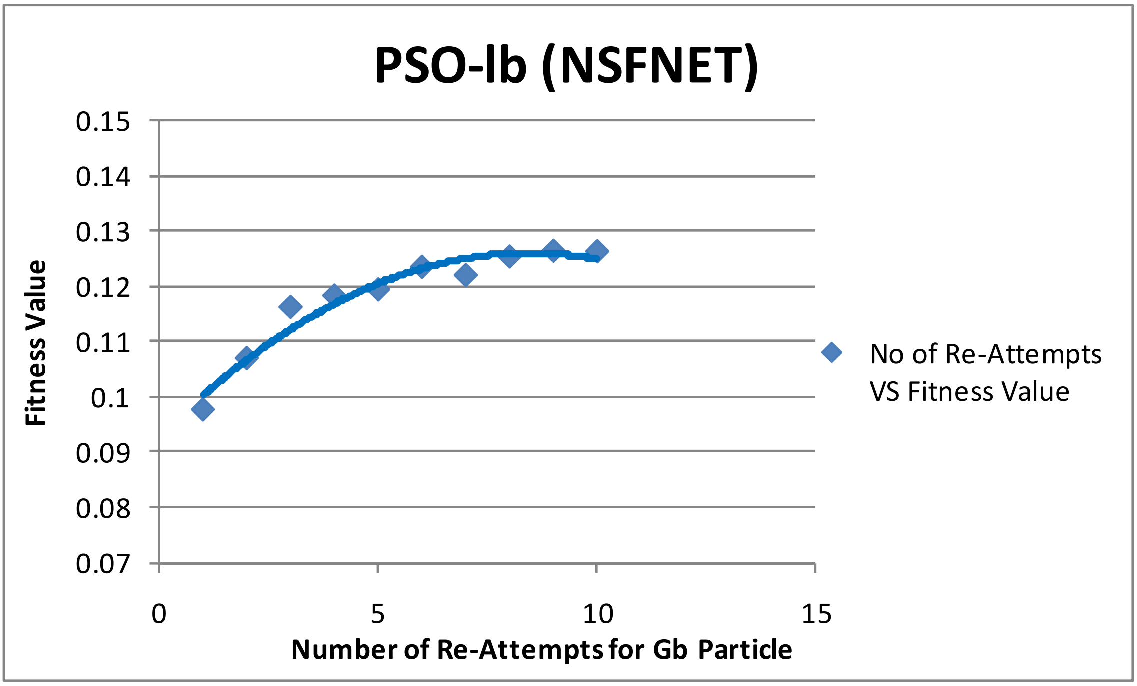


**Figure 5.16: PSO-lb performance for different number of Re-Attempts for Global Best particle in St (3), in terms of Fitness Value. Maximum number of iterations allowed = 3000, C1 = C2 = 0.05, Number of particles = 14.**

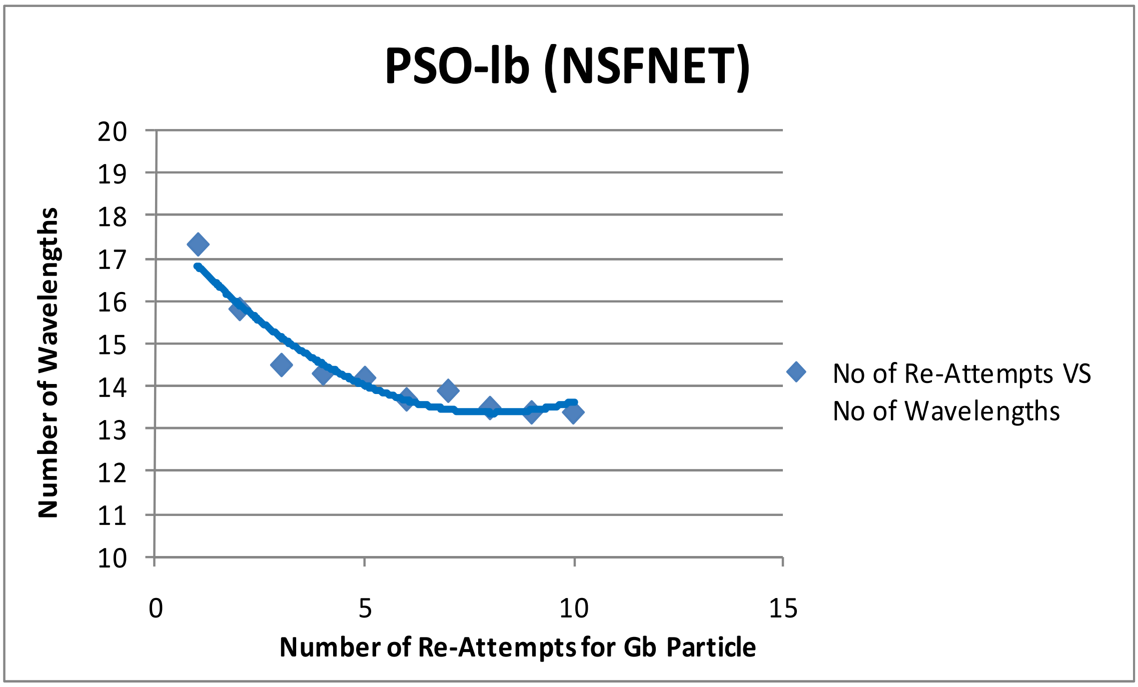


**Figure 5.17: PSO-lb performance for different number of Re-Attempts for Global Best particle in St (3), in minimum number of wavelengths required. Maximum number of iterations allowed = 3000, C1 = C2 = 0.05, Number of particles = 14.**

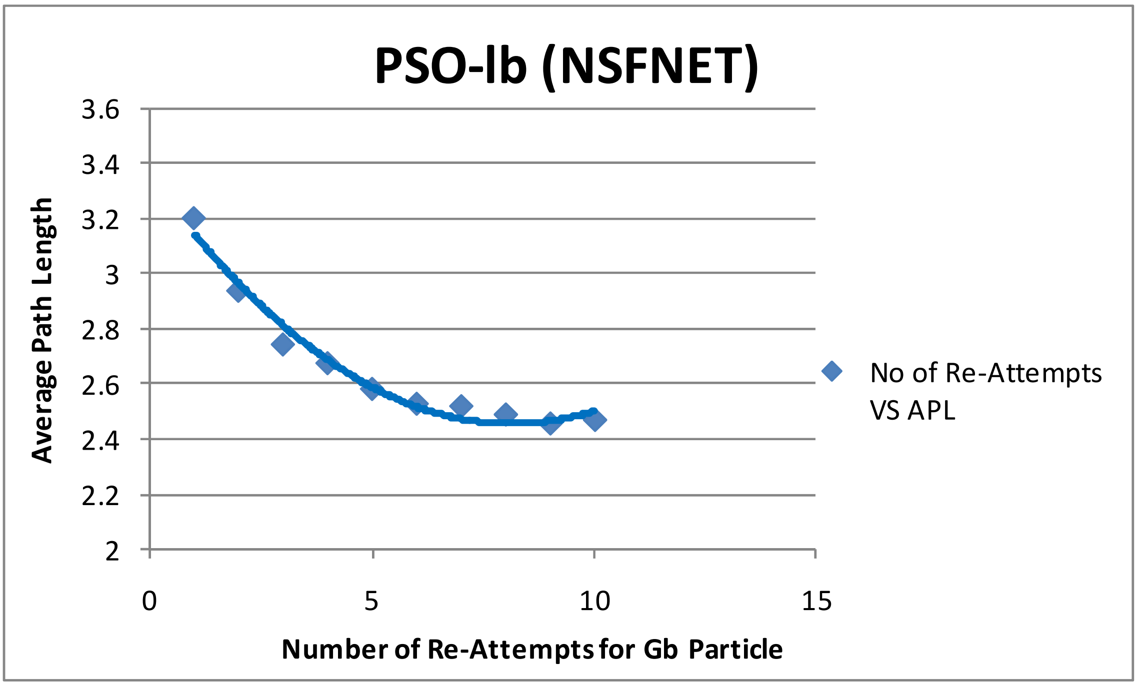


**Figure 5.18: PSO-lb performance for different number of Re-Attempts for Global Best particle in St (3), in terms of Average Path Length of the chosen routes. Maximum number of iterations allowed = 3000, C1 = C2 = 0.05, Number of particles = 14.**

Figure 5.19 also show that as the number of re-attempts is increased (i.e. between 1 and 5), it helps the swarm to avoid pre-mature convergence along with the improvement in the fitness values. The reason is that, as the number of re-attempts increase, the chances of successful replacement of highly congested routes in the particle (congestion in terms of number of connections traversing over most-loaded link in the network) increase. Subsequently, this helps swarm particles reach an optimal/near-optimal point in the problem space by avoiding local-optimal points. This behaviour can also be verified from table 5.2 and 5.3, where different combination of strategies (St.1, St. 2 and St.3) is given to observe their effect on the performance of PSO-lb. So increasing the number of re-attempts, increases the chances of highly congested route replacements carried out by strategy St. 3, during velocity computation.

However, when the value of re-attempts is increased after 5, it doesn't improve the fitness values (figure 5.16) any longer as particles have already reached the optimal-near optimal solution, rather it only help the swarm converge towards that optimal/near-optimal solution in fewer iterations. This behaviour can be seen in figure 5.16 and 5.19.

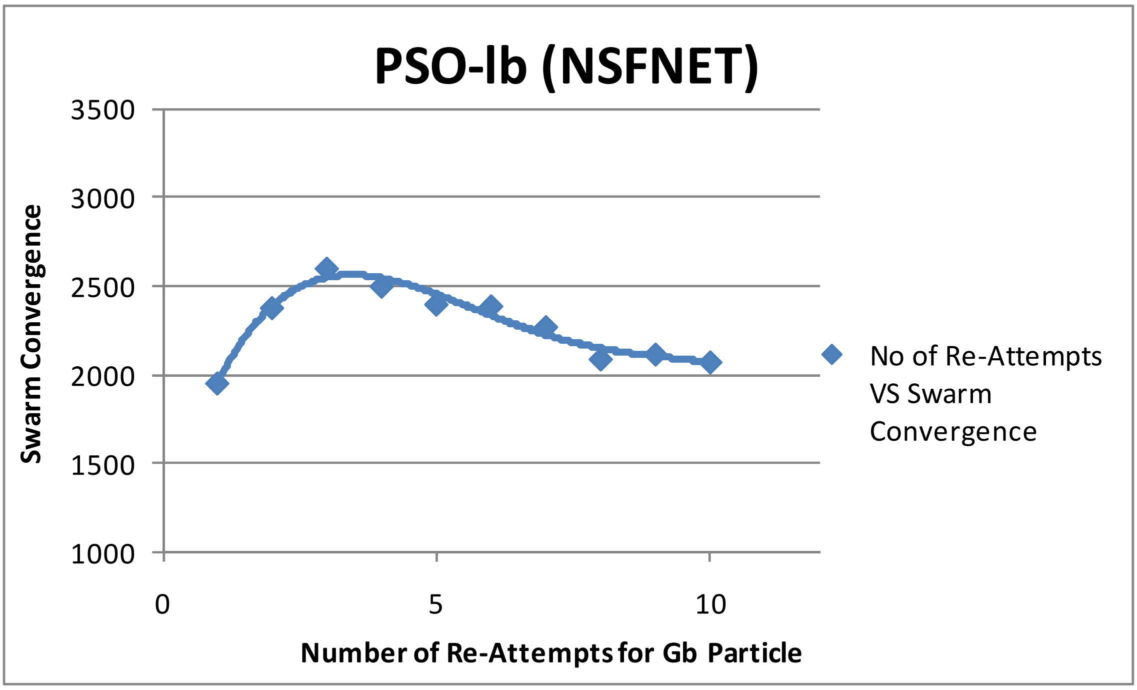


**Figure 5.19: PSO-lb performance for different number of Re-Attempts for Global Best particle in St (3), in terms of number of iterations required by the Swarm to Converge. Maximum number of iterations allowed = 3000, C1 = C2 = 0.05, Number of particles = 14.**

## 5.11. Validation and Verification of Implementation:

In order to validate the results of proposed PSO-based static RWA solver when applied to all-optical WDM networks and to verify its implementation, two different approaches are used:

(a) The proposed PSO-based static RWA is used with a small network. When all the particles in the swarm converge, the simulation is stopped. Then the results presented by the global best particle in the swarm are verified manually to make sure they satisfy 'wavelength clash constraint' and 'wavelength continuity constraint'. For example: with the wavelength clash constraint every lightpath traversing through a common edge must be assigned a unique wavelength. This can be verified by checking that in a single edge disjoint set, no network edge appears more than once. (Validation data where PSO-lb is used to solve static RWA for 14-node NSFNET for a given set of connection requests can be found in appendix B)

(b) The results presented by each particle satisfy theoretical lower bounds; $LB_w$ and $LB_{APL}$ given by equation 5.4 and 5.5, respectively.

# CHAPTER 6 IMPROVING CONVERGENCE OF PSO BASED STATIC RWA SOLVER

In the Chapter 5 a novel PSO based static-RWA solver (PSO-lb) is proposed. In the PSO-lb algorithm, the movement of the swarm particles is influenced by two main factors: (1) The position of the global-best particle in the swarm. (2) The position of the local-best particle in the swarm. An advantage of using this algorithm is that it can achieve an optimal/near-optimal solution (as shown in the table 5.1). However, one problem with the PSO-lb algorithm is that when the size of the problem space is increased by increasing the number of pre-computed k-shortest paths being employed, PSO-lb tends to converge prematurely towards a local optimum. As a result of this, the quality of the solution provided by PSO-lb deteriorates (as shown in the table 5.1, 5.2 and 5.3).

To improve the performance of the PSO based static-RWA solver and to help the swarm avoid premature convergence, a novel scheme is proposed - hereafter referred to as the PSO-pb algorithm. In PSO-pb, during the search of the problem space, each particle keeps a record of the best position it has reached so far. This position is called personal-best position of the particle. In the proposed PSO-pb scheme, the movement of the swarm particles is influenced by two factors, (However, not both at the same time i.e. not both in a single iteration of position updating of any particle in the swarm):

1. The position of Global-Best particle in the swarm (searched so far)
2. The Personal-Best position of the particle (searched so far)

The only difference between PSO-lb and PSO-pb is the way positions of the swarm particles are updated. Simulation results show that the proposed PSO-pb scheme performs better in terms of particle fitness value, number of wavelengths required for a given set of connection requests and average path length of the chosen routes as compared to PSO-lb algorithm. This is achieved by reducing the risk of premature convergence of the particles in the swarm.

## 6.1. Modified PSO Equations for Solving Static RWA in PSO-pb

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 PSO-pb 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 PSO-lb algorithm), but not both at any one time as shown in equation 6.1. 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 6.2.

$V_{i+1} = \alpha * C1\ (P_{gb} - X_i) + (1 - \alpha) * C2\ (P_{pb} - X_i)$ Equation (6.1)

$X_{i+1} = X_i + V_{i+1}$ Equation (6.2)

$\alpha$ 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.

## 6.2. 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 Chapter 5. 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.

## 6.3. Computation and Applying the Velocity

In each iteration, equation (6.1) 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 (6.2) 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 as demonstrated in the previous chapter.

## 6.4. Fitness Function

Equation 6.3 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.

$F(x) = 1 / Cost(x)$ Equation (6.3)

$Cost(x) = APL + \vartheta$ Equation (6.4)

APL = Average Path Length, $\vartheta$ = Number of 'directed edge disjoint route' sets. For a fair comparison between PSO-lb and PSO-pb algorithms, in the subsequent simulations both are assumed to be 0.5. All the routes in each of these 'directed edge disjoint route' set ($\vartheta$) can be assigned the same wavelength, as no two routes in a single set can share a common directed edge of the network. Therefore, 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.

## 6.5. 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 a 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. The third one introduces a special operation for only the global-best particle of the swarm. The three strategies, named St. (1), St. (2) and St. (3) are as follows:

- St. (1): From current particle, select those routes for replacement first, which traverse the most congested edges of the network. Congestion here is defined as number of lightpath connections traversing over an edge. The edge usage table associated with the particle can help to determine this, which is sorted according of edge congestions. St (1) starts with first edge and tries to find the routes for replacements. If, sufficient routes can't be selected from the first edge, next edge is selected and so on.

- St. (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 of the most loaded link (i.e. congested link) in the alternative route is lower than the congestion of the most loaded link in the previously assigned route.
- St. (3): For the 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 chapter, the value of 't' is assumed to be 4)

## 6.6. Pseudo Code for the Proposed PSO-based static RWA (PSO-pb) Algorithm:

- Initialization (for each particle):
    - Randomly select a route (from pre-computed K-shortest paths) for each connection request, and assign it to the particle.
    - Apply the fitness function to quantize the particle in terms of its fitness value.
    - Mark the particle having best fitness value in the whole swarm as global-best.
    - Mark this position as personal-best of the particle.
- For each particle Do:
    - Find the velocity for the particle according to the position of global-best particle or personal-best position of the particle (searched so far). This will

give the number of routes in current particle that needs to be replaced in the current particle by routes from global-best or personal-best particle, ‘y’.

    - Consult the ‘common edge usage table’ of the particle, and select ‘n’ routes which are different in both the particles and traverse through the most congested edges on the network (Only St (1) is used here).
    - Replace those routes in the current particle with the corresponding routes in the position of global-best particle or personal-best position of the particle.

- At the end of each iteration, re-apply the fitness function to update the global-best particle. If the new position of the particle has better fitness value as compared to the personal-best position, update the personal-best position of the particle.
- Iterate for a pre-defined number of iterations or until the swarm converges.

## 6.7. Simulation Results and Analysis

A simulator has been implemented in Opnet™ (http://www.opnet.com) to evaluate and compare the performance of proposed PSO-pb algorithm using personal-best and global-best search, for solving static RWA in All-Optical WDM networks shown in Figures 4.2 and 5.4. A theoretical lower bound on the ‘number of wavelengths required’ and lower bound on ‘average path length’ presented in Chapter 5 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 *‘Mersenne Twister’* Generalized Feedback Shift Register (GFSR) pseudo random number generator is used for the simulations due to its properties including its long period [103]. Each simulation is carried out 15 times using different seed values and the averages are reported here.

In order to perform a comparison between PSO-pb and PSO-lb, the size of problem search space is increased by increasing the number of pre-computed k-shortest paths (Number of KSP) considered. The results are summarized in table 6.1. It shows the proposed PSO-pb scheme achieves near-optimal solutions when compared with the theoretical bounds on the number of wavelengths required and the average path length of the chosen routes. In the case of PSO-pb, since there’s no influence of local-best particle of the local neighbourhood, the ‘NS’ (Neighbourhood Size) is not applicable. Table 6.1 also shows that PSO-pb performs better than PSO-lb in terms of number of wavelengths required for a given set of connection requests and the average path lengths of the chosen routes. PSO-pb performs better by avoiding premature convergence as evident from the 'iteration number of the last improvement' in the fitness value of the global-best particle.

**Table 6.1: Experimental results of PSO-pb VS PSO-lb for static RWA for networks shown in the figure 4.2 and 5.4. All three strategies, St. (1), St. (2) & St. (3) are used. Number of KSP = 8.**

| | Algorithm Used | Swarm Size | NS | Social Learning Parameter | No of GB Re-attempts 't' | Iteration # of Last Improvement | APL | ϑ |
|---|---|---|---|---|---|---|---|---|
| **NSFNET (Figure 4.2) *$LB_W$* = 13 *$LB_{APL}$= 2.14*** | PSO-lb | 14 | 3 | C1 = 0.05<br>C2 = 0.05 | 4 | 2329.33 | 2.676 | 14.26 |
| | PSO-pb | 14 | N/A | C1 = 0.05<br>C2 = 0.05 | 4 | 5085.8 | 2.432 | 13.46 |
| **EON (Figure 5.4) *$LB_W$* = 18 *$LB_{APL}$= 2.36*** | PSO-lb | 18 | 3 | C1 = 0.05<br>C2 = 0.05 | 4 | 3280.2 | 2.971 | 18.8 |
| | PSO-pb | 18 | N/A | C1 = 0.05<br>C2 = 0.05 | 4 | 12181 | 2.805 | 18.1 |

In order to analyse the effect of different swarm sizes on the performance of PSO-pb and PSO-lb, a set of simulations are conducted. In each case, all three strategies mentioned in section 6.5 are used here with both PSO-pb and PSO-lb. In case of PSO-lb, the swarm size is assumed to be 3. The number of connection requests in the given set is equal to N*(N-1) where 'N' is the number of nodes in the network. For a fair comparison between PSO-pb and PSO-lb, all network and algorithmic conditions are kept the same. As shown in figure 6.1, PSO-pb performs considerably better in terms of fitness value as compared to PSO-lb for solving the static RWA problem, for various swarm sizes. The same trend can be seen in figure 6.4, where the EON network is considered.

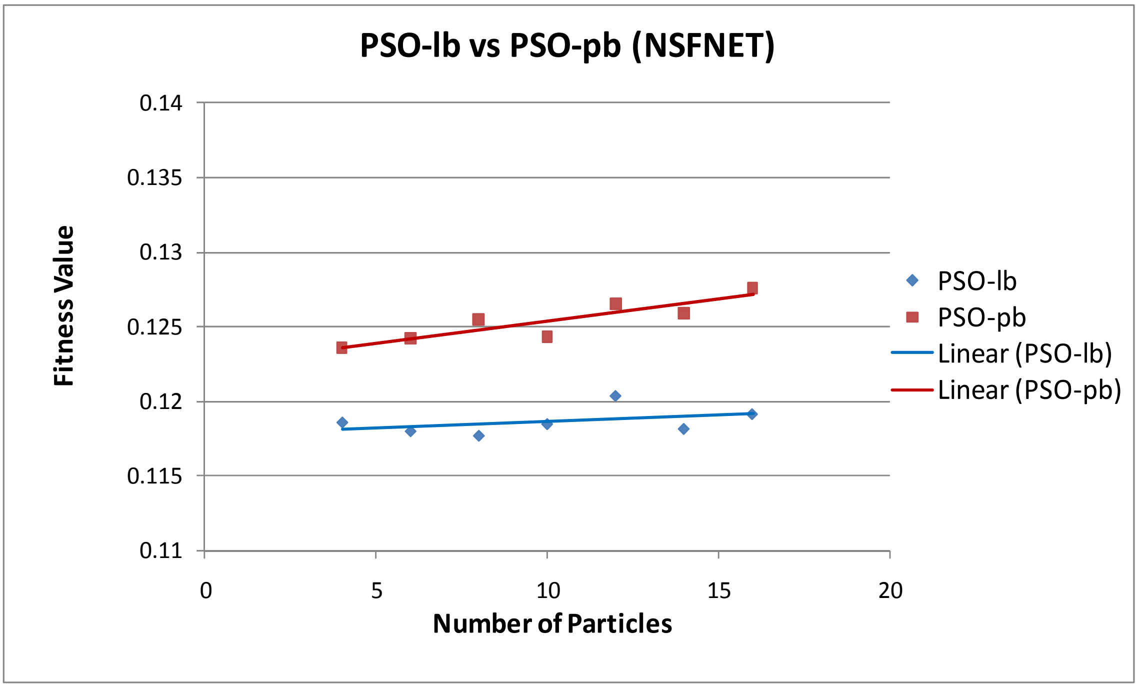


**Figure 6.1: Performance comparison between PSO-lb and PSO-pb in terms of Fitness Value of the global best particle and number of particles in the swarm. NSFNET (figure 4.2) is used. Number of KSP = 8, Number of re-attempt 't' = 4 (St. 3), $C_1 = C_2 = 0.05$.**

The main reason of superior performance of PSO-pb algorithm as compared to PSO-lb, in terms of fitness value of the global best particle, is its ability to avoid premature convergence. Figure 6.1 clearly shows that when the number of particles in the swarm is varied, the fitness value in case of PSO-pb continues to improve as compared to PSO-lb. In case of PSO-lb, there's more tendency of the swarm to converge to a local optimum. Therefore, the improvement in the fitness value halts comparatively quickly as compared to PSO-pb. The same trend can be observed in figure 6.4 where EON network is considered.

Figure 6.2 shows the result of an experiment carried out to compare the performance of PSO-lb and PSO-pb in terms of iteration number when last improvement is made in the fitness value of the best particle in the swarm, for various swarm sizes. This figure shows that in all the cases, PSO-pb performs better as compared to PSO-lb as PSO-pb algorithm continue to show improvement in the best fitness value of the swarm. On the other hand, PSO-lb tends to converge towards local optimal-solution relatively quickly as compared to PSO-pb algorithm. Same trend can be observed in figure 6.5 where EON network is assumed.

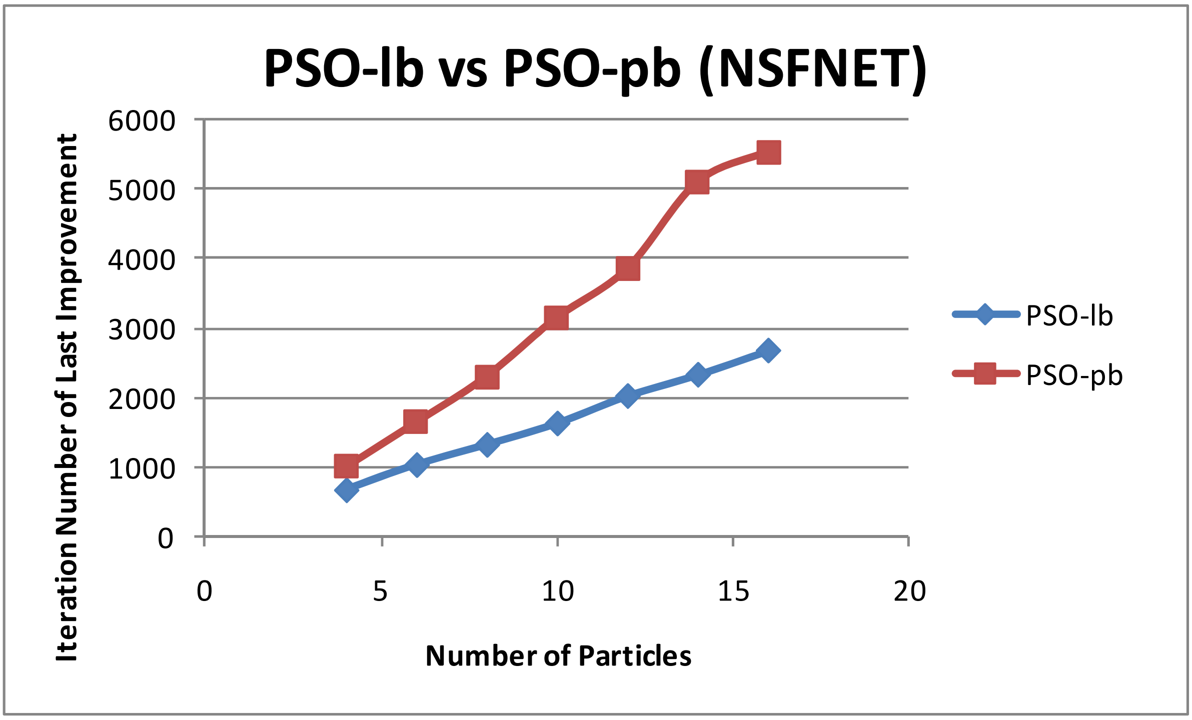


**Figure 6.2: Performance comparison between PSO-lb and PSO-pb in terms of Iteration number of the last improvement in the fitness value and number of particles in the swarm. NSFNET (figure 4.2) is used. Number of KSP = 8, Number of re-attempt 't' = 4 (St. 3), $C_1 = C_2 = 0.05$.**

Figure 6.3 confirms the reason of superior performance of PSO-pb as compared to PSO-lb. In the case of PSO-lb algorithm, the swarm has a tendency to converge relatively quickly as compared to PSO-pb. This causes the swarm particle to be stuck in local optimum solution unlike PSO-pb. This shows that the particle movement in the problem search space guided by personal-best position of the particle and position of global-best particle, can avoid locally optimum points better as compared to a search where the movement of the particles is influenced by positions of local-best and global-best particle. The same trend can be observed in figure 6.6, where the EON network is considered.

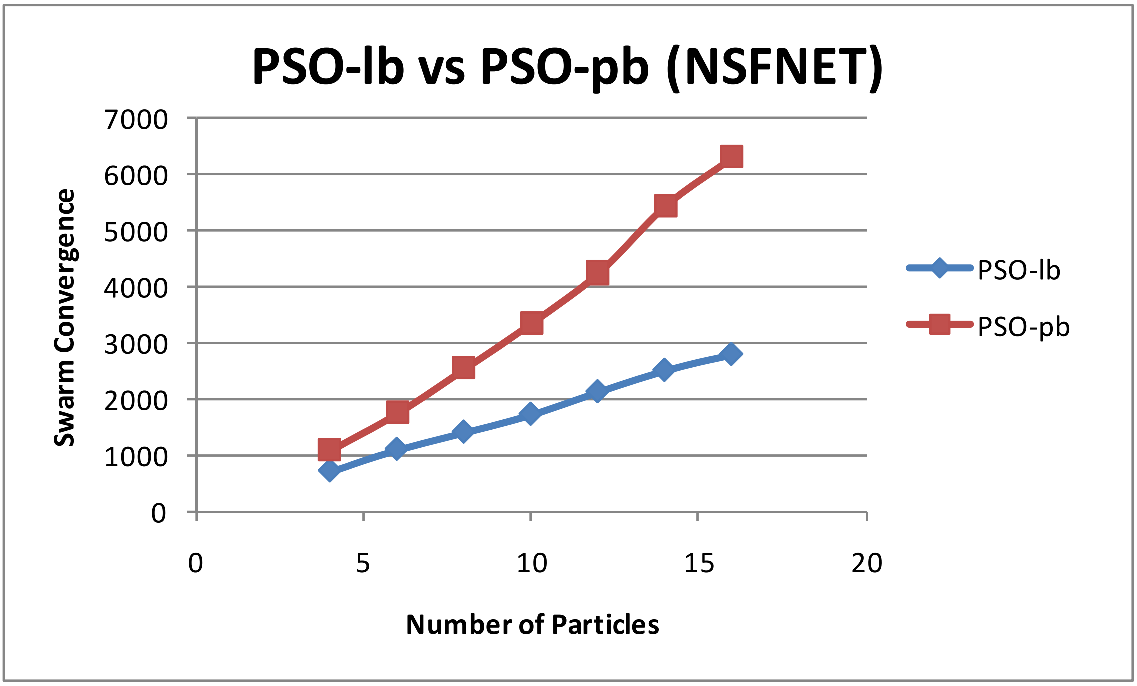


**Figure 6.3: Performance comparison between PSO-lb and PSO-pb in terms of Number of iterations taken by the swarm to converge and number of particles in the swarm. NSFNET (figure 4.2) is used. Number of KSP = 8, Number of re-attempt 't' = 4 (St. 3), $C_1 = C_2 = 0.05$.**

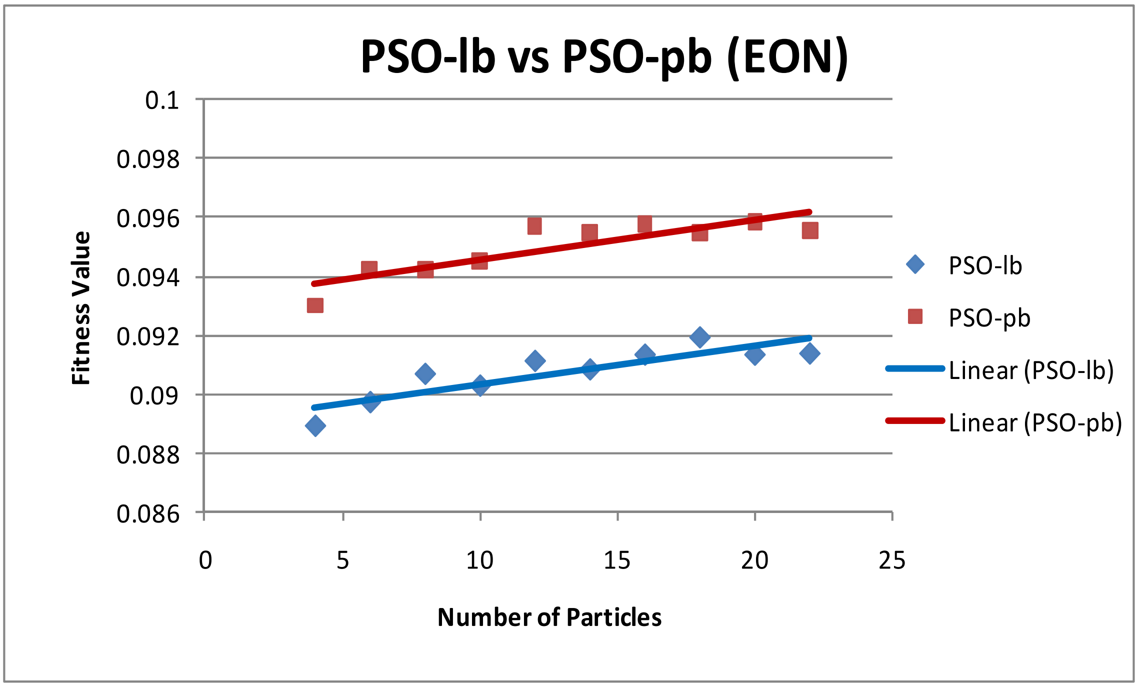


**Figure 6.4: Performance comparison between PSO-lb and PSO-pb in terms of Fitness Value of the global best particle and number of particles in the swarm. EON (figure 5.4) is used. Number of KSP = 8, Number of re-attempt 't' = 4 (St. 3), $C_1 = C_2 = 0.05$.**

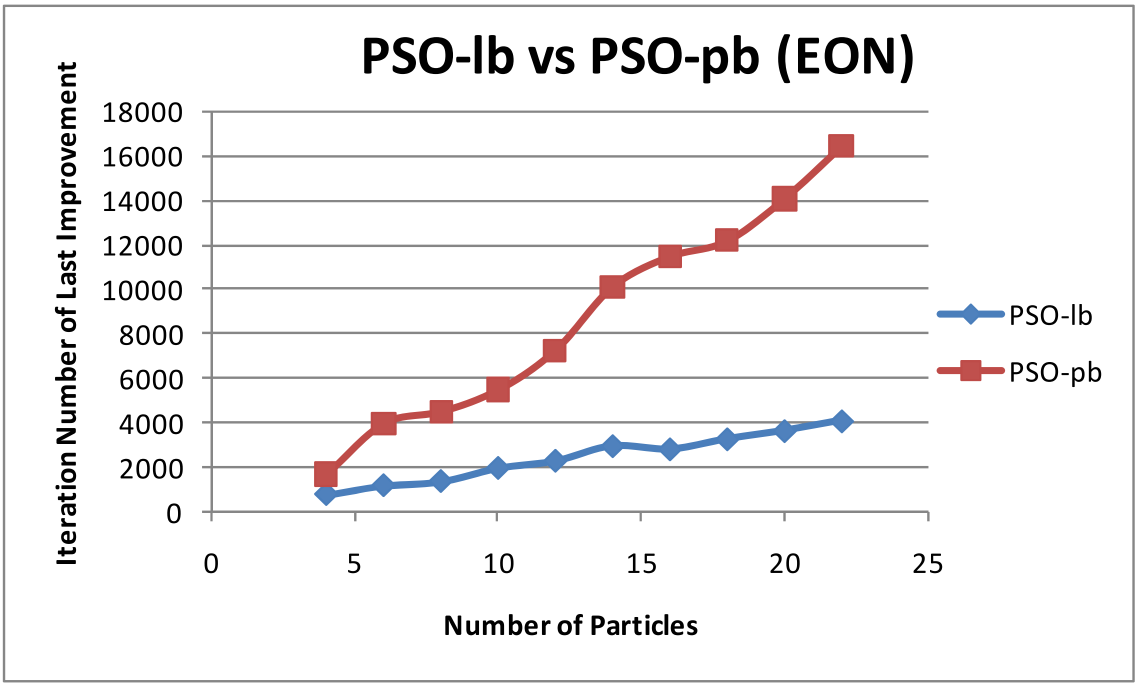


**Figure 6.5: Performance comparison between PSO-lb and PSO-pb in terms of Iteration number of the last improvement in the fitness value and number of particles in the swarm. EON (figure 5.4) is used. KSP = 8, Re-attempts 't' = 4 (St.3), $C_1$=$C_2$=0.05.**

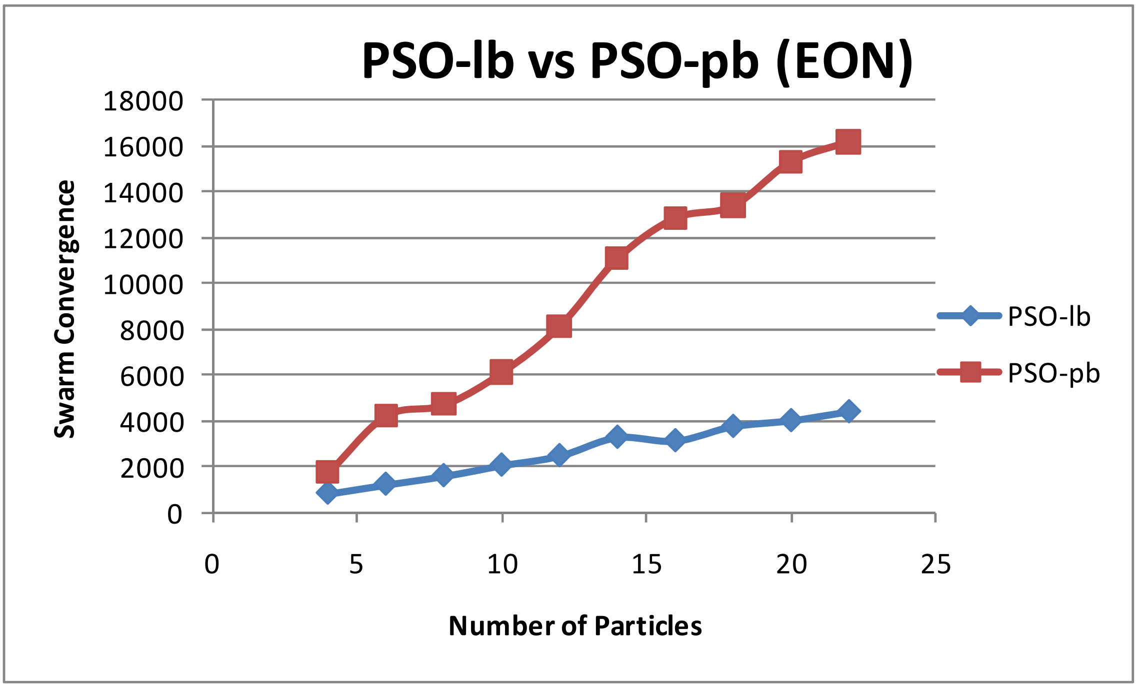


**Figure 6.6: Performance comparison between PSO-lb and PSO-pb in terms of Number of iterations taken by the swarm to converge and number of particles in the swarm. EON (figure 5.4) is used. Number of KSP = 8, Number of re-attempt 't' = 4 (St. 3), $C_1$ = $C_2$ = 0.05.**

## 6.8. Conclusion

In this chapter a PSO-based RWA solver PSO-pb 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 PSO-lb algorithm, where the 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 PSO-pb performs better in terms of fitness value as compared to PSO-lb by reduces the risk of premature convergence. This also shows the ability of PSO-pb to avoid locally optimal solutions more often when compared to PSO-lb.

# CHAPTER 7 PSO BASED DYNAMIC ROUTING AND WAVELENGTH ASSIGNMENT (DYNAMIC TRAFFIC CASE)

In this chapter, a novel particle swarm optimization (PSO) based scheme inspired by swarm intelligence is proposed to provide DRWA under the wavelength continuity constraint. The First-Fit (FF) algorithm is chosen for wavelength assignment, as it is simple to implement as compared to schemes like Max-Sum and Relative Capacity Loss (RCL). Also the performance difference among various wavelength assignment schemes is not very large [108].

Some of the novelties of this work are:

- Using Particle Swarm Optimization to solve dynamic RWA problem for All-Optical WDM networks without any wavelength conversion capability.
- Novel fitness function simultaneously takes into account both the hop-length of the chosen route and number of free wavelengths available over the whole route.
- The proposed fitness function significantly reduces the need to have dynamically adjustable 'α' factor which is used to control the influence of hop-length and number of free wavelengths, on the fitness value of the particle.

## 7.1. General PSO Algorithm

PSO is a population based optimization technique, developed by Kennedy and Eberhart [60, 61], inspired by social behaviour of bird flocking (and schools of fish). In PSO, a swarm is a collection of particles where each particle has both a position and velocity. The position of the particle represents a candidate solution to the problem space while the velocity is used to move the particle from one position to another. The "classical" PSO equation where the position and velocity represents physical attributes of the particles is represented by Equation (7.1) and Equation (7.2).

Calculating a Single Particle's New Velocity:

$$V_{id} = V_{id} + \eta_1 r_1 (P_{id} - X_{id}) + \eta_2 r_2 (P_{id}^{n} - X_{id})$$
$$where \quad i = 1,2,...N. \; d = 1,2,...D$$

Equation (7.1)

"Moving" a Single Particle in a Swarm

$$X_{id} = X_{id} + V_{id}$$

Equation (7.2)

$P_{id}$ is the personal best position, a particle has reached; $P_{id}^{n}$ is the global best position of all the particles. $\eta_1$ (the self-confidence factor) and $\eta_2$ (the swarm-confidence factor) are positive constants called '*acceleration constants'* to determine the influence of $P_{id}$ and $P_{id}^{n}$; $r_1$ and $r_2$ are independent random numbers in the range [0, 1]. N is the total number of particles in the swarm and D is the dimension of the problem search space.

PSO starts by randomly initializing the position and velocities of all the particles in the swarm over the problem space. The position of $i^{th}$ particle is represented by the vector $X_i = [X_{i1}, X_{i2} \ldots X_{iD}]$ and velocity of $i^{th}$ particle is represented by the vector $V_i = [V_{i1}, V_{i2} \ldots V_{iD}]$, where D is the number of function parameters being optimized. For each iteration (until the convergence criteria is met), the fitness function is applied to the particles to quantize their respective positions over the problem search space. The particle with the best fitness value in the neighbourhood is marked as the global/local best particle. Each particle will also keep a record of its personal best position searched so far. Equation (7.1) is used to calculate new velocity for each particle in the swarm based on particle's previous velocity, its current and personal best position, and the position of the particle with best fitness value in the neighbourhood. Equation (7.2) is then used to apply the velocity to the particle. As a result of this, the particle will move to a new position i.e. it will now represent a new candidate solution to the problem being studied.

## 7.2. Related work

Evolutionary optimization schemes like genetic algorithms (GA) and PSO have successfully been used in the past to solve many NP-hard optimization problems [45]. GA and PSO are similar in the way that both techniques are population-based search schemes that mimic the natural biological evolution and/or the social behaviour of species [45, 78]. Each member of the population represents a candidate solution to the problem addressed, and over time they evolve to represent some other candidate solution. One advantage of PSO over GA is that PSO is more computationally efficient [79]. Some performance comparison studies between GA and PSO have been reported in [78, 79, 80, and 81].

In [108], a novel GA based scheme is proposed to solve dynamic RWA problem in wavelength routed optical networks. Genetic algorithms are swarm intelligence inspired search schemes based on the idea of natural selection and natural genetics. In [108], a member of the population (gene) represents a route from source to destination node i.e. a candidate solution to the routing sub-problem for DRWA. Genetic operators like crossover, mutation and then selection are applied to create a new population of genes. Ammar *et al* [109] have proposed a hybrid algorithm based on PSO and a noising meta-heuristic for computing shortest paths in the network. The hybrid PSO based scheme shows better performance as compared to GA-based search algorithms for optimal shortest path computation [109]. In [108] and [110], GA algorithms are proposed for solving DRWA in all-optical WDM networks. In this chapter, the GA based schemes proposed in [108, 110] and shortest path routing with first-fit heuristic algorithm are selected as the schemes for performance comparison purposes with our novel PSO-based algorithm.

## 7.3. Proposed PSO scheme for Dynamic Routing and Wavelength Assignment (Dynamic RWA)

This section describes the proposed PSO-based scheme for solving the DRWA problem for all-optical networks with the wavelength continuity constraint applied.

### 7.3.1. Encoding and Decoding of Particle in the Swarm

A typical encoding scheme for path representation is the 'direct-representation' scheme [109] where a path is represented as a sequence of node identification numbers from the source node to the destination node. Encoding schemes based on direct representation have been used to encode paths in [111]. Gen *et al* [112] proposed an indirect-representation scheme (priority-based encoding) for solving the shortest path problem using GA. In the priority-based encoding scheme, a path (chromosome) is represented by encoding some guiding information about a node instead of the node-ID. An example of such guiding information can be the node priority. This guiding information is used to generate a path from an arbitrary chromosome. In [113] a 'weighted encoding scheme' is used for chromosome representation in GA, whereas in [109], a cost-priority based encoding scheme is used for representing a particle in PSO which helps the particle to converge towards a shorter path quickly.

In the proposed dynamic RWA scheme, the objective is not to compute a shortest path from source to destination node of the lightpath request. Instead the objective is to compute a path, which improves the blocking probability performance of the dynamic RWA algorithm, for the future connection requests. Therefore, for simplicity, a priority based encoding scheme is used. The position of the particle is represented as a vector of node priorities. The path, which a particle represents, is decoded using a path growth procedure [112] by starting from the source node and then sequentially appending the intermediate nodes one-by-one, till the destination node is reached. During the path growth procedure, if more than one node is available, the node with the highest node priority is selected. Every time as node is selected during path construction, it is marked as unavailable for the rest of path growth procedure. Figure 7.1 illustrates an example of priority based encoding, where a path is being constructed for a lightpath request between source node '1' and destination node '9' in NSFNET (previously shown in Figure 4.2) by decoding the position of the particle using the 'path growth' procedure.

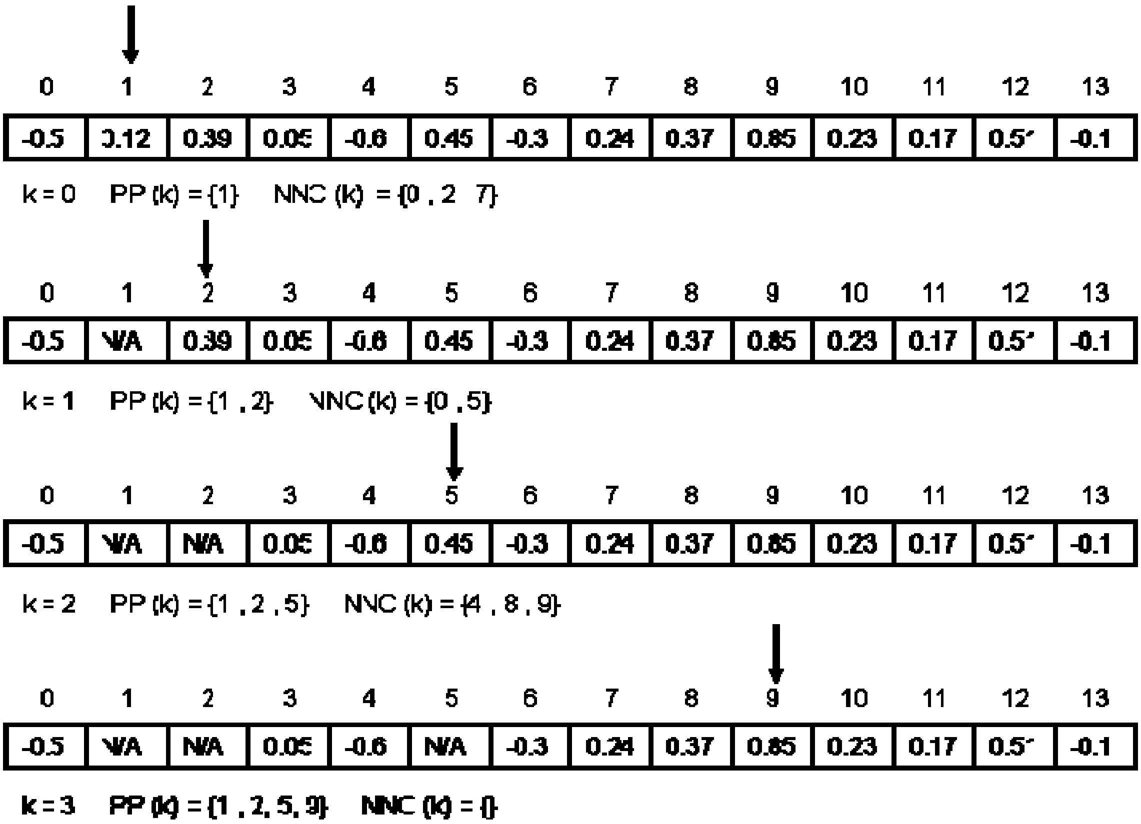


**Figure 7.1: Priority based encoding and Path growth procedure for decoding. k = iteration number. PP (k) is the 'partial path vector' at iteration 'k'. NNC (k) is the 'next node candidate' vector.**

### 7.3.2. Neighbourhood topology - Global:

In PSO, the particle's movement through the search space is influenced by the particle's own experience and the experience of the most successful particle in its neighbourhood. A neighbourhood is a set of particles in the swarm whose positions will influence a particle's own search due to their proximity to the particle. In the proposed PSO scheme for dynamic RWA, a global neighbourhood is used where all the members in the swarm are particle's neighbours. So the movement of a particle through the problem space is determined by the best position searched by the particle itself (searched so far) and the position of the particle having best fitness value (searched so far) in the whole swarm.

### 7.3.3. Swarm initialization:

In the swarm, ‘p’ particles are created. After creation of particles, they need to be initialized. In the proposed PSO algorithm, each particle’s position (node priorities) and the velocity are randomly initialized with real numbers in the range [-1.0, 1.0]. In order to avoid the velocity from becoming very large in the initial PSO iteration, and to avoid premature convergence to a local optimum as well as to restrict the influence of particle’s old velocity on the current velocity, a number of improvements are suggested in the literature [114, 115, 116, 117]. For example, Clerc [63] proposed the use of constriction factor $\chi$ in order to prevent large velocity values. This constriction factor has been used successfully along with PSO by many researchers to solve different NP-hard problems. Therefore, the general equation to compute new velocity of the particle (given by equation 7.1) has been modified to include constriction factor.

Equation (7.3) is used here velocity computation for a particle.

$$V_{id} = \chi[V_{id} + \eta_1 r_1 (P_{id} - X_{id}) + \eta_2 r_2 (P_{id}^n - X_{id})]$$
$$where \quad i = 1,2,...N.\ d = 1,2,...D$$

Equation (7.3)

Where,

$$\chi = 2 * \left( \left| 2 - \eta - \sqrt{\eta^2 - 4\eta} \right| \right)^{-1} \quad if\ \eta = \eta_1 + \eta_2 > 4$$

Equation (7.4)

### 7.3.4. Fitness Function:

For solving dynamic RWA problem, a novel fitness function is used which takes into account not only the normalized length of the route i.e. number of hops between the source and destination node. It also considers the normalized number of free wavelengths available over the whole route while satisfying wavelength continuity constraint. If no free wavelength is available for the route selected, then the fitness function will assign a large negative fitness value (-100.0) for that particle.

$L_{max}$ is the maximum length of the route between any source – destination pair and $L_{sd}$ is the length of the route between source 's' and destination 'd'. α [0, 1] is a design parameter, and $W_{Total}$ is the total number of wavelengths supported by the optical network. $W_{sd}$ then defines the number of free wavelengths available over the route between source 's' and destination 'd'. The fitness function used here is then represented by Equation (7.5).

$$F(i) = \begin{cases} \left[\alpha * \frac{(L_{\max} - L_{sd})}{L_{\max}}\right] + \left[(1-\alpha) * \left(1 - \frac{W_{Total} - W_{sd}}{W_{Total}}\right)\right] & \text{if } W_{sd} > 0 \,\&\, W_{sd} < W_{Total} \\ \left[\alpha * \frac{(L_{\max} - L_{sd})}{L_{\max}}\right] + \left[(1-\alpha)\right] & \text{if } W_{sd} = W_{Total} \\ -100.0 & \text{if } W_{sd} = 0 \end{cases}$$

Equation (7.5)

## 7.5. Simulation Results and Analysis

In order to evaluate the performance of the proposed PSO based scheme (hereafter simply referred as the PSO algorithm) for solve dynamic RWA problem in terms of connection blocking probability and route computation time, a simulator has been implemented in Opnet Modeler™ [118] on a Dell optiplex GX520 machine having 3.00 GHz processor and 2 GB of RAM in windows environment. 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 [103].

### 7.5.1. Connection Provisioning for Incremental Traffic

To evaluate the performance of PSO in terms of connection provisioning as compared to other dynamic RWA schemes, an experiment is conducted where the connections are added incrementally. Incremental traffic is considered here which means that the connections arrive one-by-one and stay in the network for an infinite amount of time. The simulation is stopped when the first connection request is blocked because of unavailability of resources (Lack of wavelength availability). A centralized traffic source generator is assumed where connection requests are arrived and provisioned incrementally. Also all the computation relating to routing and wavelength assignment is done at a centralized node where signalling latency to and from this node is assumed to be zero.

The objective of this experiment is to examine that for a given number of wavelengths, what is the maximum number of connections that can be provisioned or supported over the network. The source and destination nodes are chosen randomly with uniform distribution. 16 nodes NSFNET shown in figure 5.5 is assumed here. The connection provisioning performance of PSO is examined relative to SP-MU (Shortest Path with Most Used wavelength assignment algorithm), SP-MU sorted (Shortest Path with Most Used wavelength assignment algorithm where the routes are sorted according to the hop-length), SP-FF (Shortest Path with First Fit wavelength assignment algorithm) and ACO [96] (Ant Colony Optimization) algorithm as shown in figure 7.2.

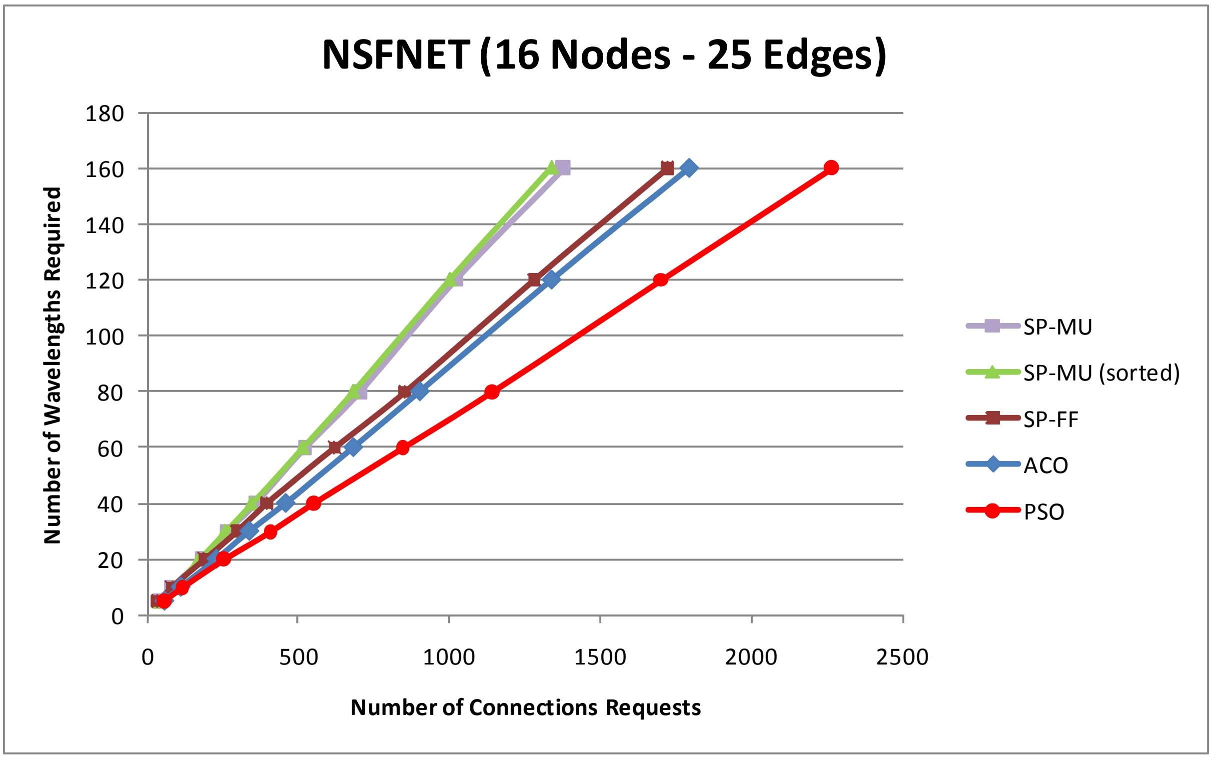


**Figure 7.2: Number of connections that can be set-up for a given number of wavelengths. 16-Node NSFNET (figure 5.5) is considered here. For PSO, number of particles = 16, number of iterations allowed (for each particle) = 20, 'α' = 0.5.**

Figure 7.2 clearly shows that the PSO algorithm performs significantly better as compared to other algorithms as it can provision more connection requests for a given number of connection requests in almost all the cases. The main reason of better performance is the proposed fitness function being used with PSO which spreads the network load such that more connections can be accommodated for a given number of wavelengths supported by the optical fibres (edges) of the network.

### 7.5.2. Blocking Probability Performance Using Randomly Distributed Traffic

The performance of any dynamic routing and wavelength assignment algorithm is generally determined by measuring the blocking probability for the future connection requests. To compare the performance of proposed PSO algorithm in terms of blocking probability, the Genetic Algorithms proposed in [108] and [110] are employed (hereafter simply referred to as GA1 and GA2 algorithms respectively). Blocking probability performance of the PSO algorithm is also compared with a shortest path algorithm with first-fit wavelength assignment algorithm (hereafter simply referred to as the SP_FF algorithm). Experiments are conducted for NSFNET and EON networks shown in the Figure 4.2 and 5.4 respectively, without any wavelength conversion capability. WDM links of these All-Optical networks are either assumed to have a capacity of 8 and 16 wavelengths, as indicated.

The main motive in choosing the two genetic based algorithms for comparison with proposed PSO based scheme for all-optical WDM networks without any wavelength conversion capability are:

- PSO is an evolutionary scheme belonging to the class of swarm intelligence algorithm. So it is more appropriate to produce comparisons with well-established alternative evolutionary algorithms that provide an easily understood baseline.
- Since the publication of these two GA based schemes, there has been nothing relevant published. These two schemes are still regarded as benchmarks where genetic algorithms are used to solve dynamic RWA problem in all-optical WDM networks without any wavelength continuity constraint.

For a fair comparison between PSO and GA algorithms, the swarm population sizes i.e. number of particles in the case of PSO and the number of chromosomes in the case of GA algorithms are kept the same. Also the number of evolutionary iterations i.e. the number of PSO iterations allowed per particle is kept as same as that of number of generations in the case of GA.

For simulations, a dynamic traffic model is used where connection requests were generated at each node following a Poisson process with an arrival rate of $\lambda_{nodes}$ (connection arrivals / time unit). Destination nodes for the connections are randomly chosen according to a uniform distribution. Therefore, the total connection arrival rate ($\lambda_{total}$) in the whole network is the product of total number of nodes in the network and $\lambda_{nodes}$.

If φ is the total number nodes in the network, then

$$\lambda_{total} = \varphi * \lambda_{nodes}$$ Equation (7.6)

The connection holding time is exponentially distributed with mean 'T' seconds. Therefore, the traffic load is given by Equation (7.7).

$$Traffic\ Load = \lambda_{total} * T \Big/ \varphi * (\varphi - 1)$$ Equation (7.7)

For the experiments, the value of 'T' is kept constant at 50 seconds and the value of $\lambda_{nodes}$ is changed in order to vary the value of traffic load. A distributed control system is used where each node in the network upon a connection request arrival performs a dynamic routing and wavelength assignment computation (using out-of-band signalling). For the wavelength assignment, DIR (destination-initiated reservation) [119] along with a first-fit algorithm is used. This requires three control packets to be sent along the chosen route for connection establishment; one for checking wavelength availability, the second for wavelength reservation and the third for confirmation of the lightpath establishment. Each node is assumed to have wavelength usage information of the whole network. No alternative routing is used and no re-attempts are made for route re-computation. So if the chosen route cannot find a free wavelength, the connection will be blocked. For different traffic loads, each experiment is carried out 15 times with different seeds for the random number generator and the mean values are plotted in the figure 7.3, 7.4, 7.5 and 7.6 along with the 95% confidence intervals.

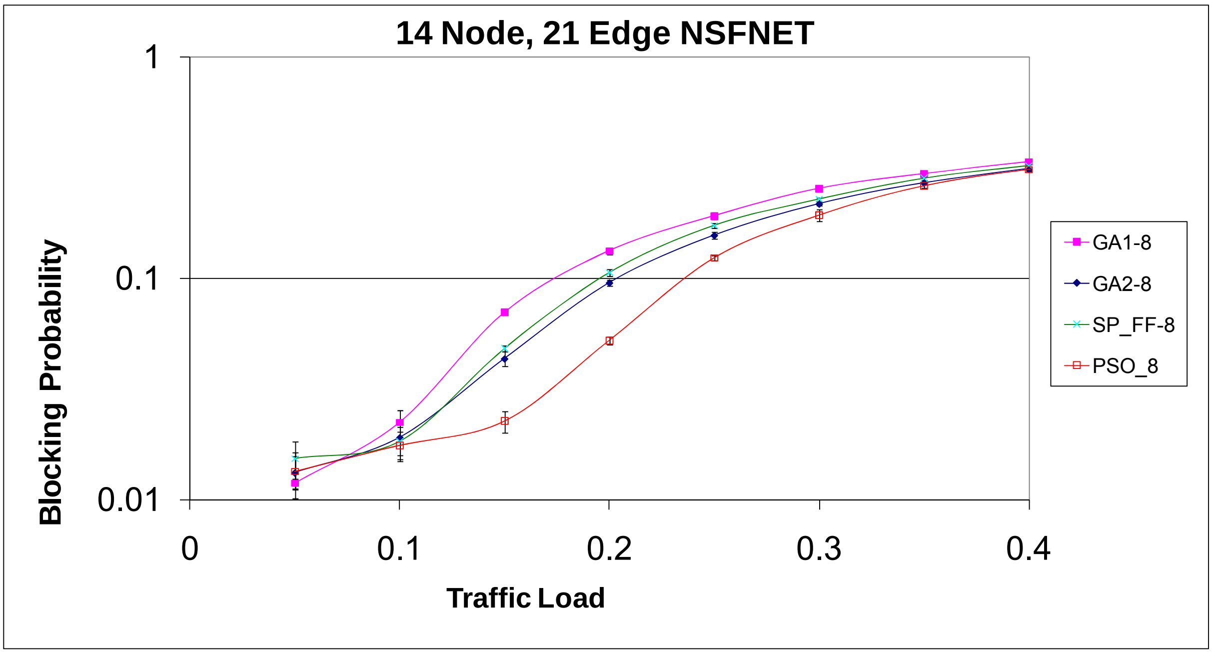


**Figure 7.3: Blocking Probability Versus Traffic load between PSO, GA1, GA2 and SP_FF algorithms for NSFNET (Figure 4.2). Number of Wavelengths = 8, α = 0.9, Confidence Interval = 95%, Population size (for both GA and PSO algorithms) = 15, Iterations/particle (PSO) = 20, Generations (GA) = 20.**

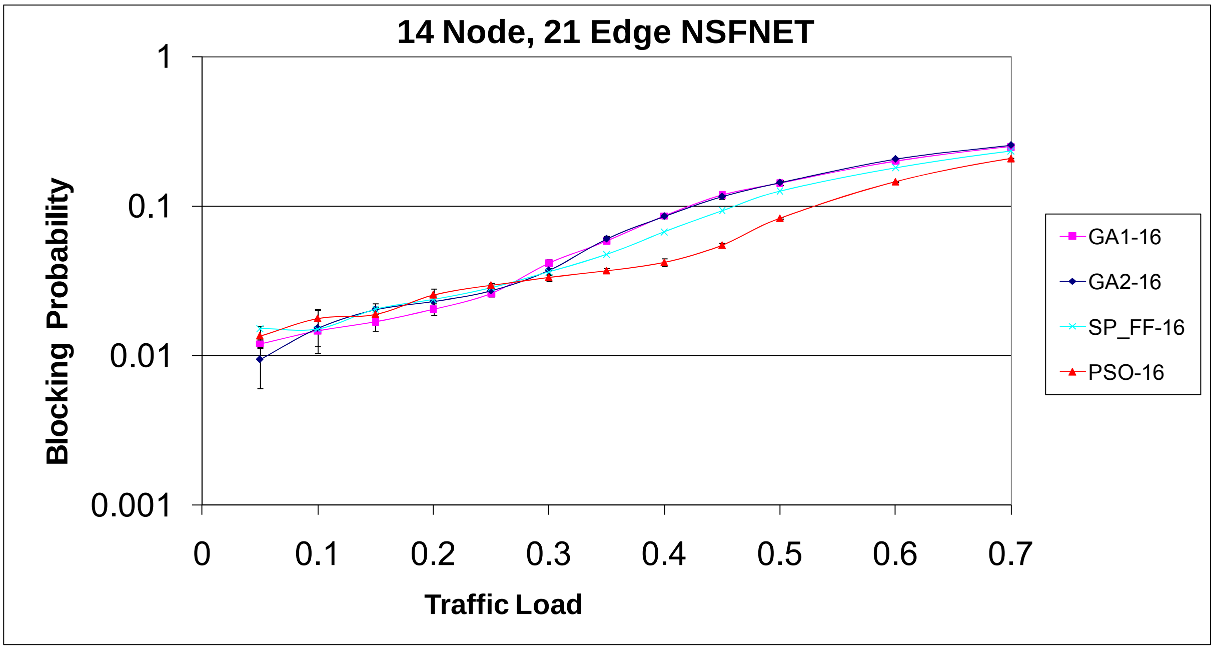


**Figure 7.4: Blocking Probability Versus Traffic load between PSO, GA1, GA2 and SP_FF algorithms for NSFNET (Figure 4.2). Number of Wavelengths = 16, α = 0.9, Confidence Interval = 95%, Population size (for both GA and PSO algorithms) = 15, Iterations /particle (PSO) = 20, Generations (GA) = 20.**

Figure 7.3 and 7.4 shows the relationship of blocking probability versus the traffic load for 8 and 16 wavelength variants of the NSFNET network respectively. As shown in Figure 7.3, when the wavelength capacity is 8 per link, all schemes show similar blocking probability performance at low traffic loads i.e. between the traffic loads of 0.05 and 0.1. The reason is, at low traffic loads, these schemes can always find free wavelengths to be assigned whatever route they choose. When the traffic load is increased i.e. between 0.1 and 0.35, the PSO scheme shows a significant performance improvement in terms of blocking probability. However, when the traffic loads is increased above 0.4, both GAs and PSO tend to the same blocking performance. The reason is, at very high traffic loads, links become saturated and the availability of free wavelengths becomes very limited as most of the wavelengths are already being used in the network.

In Figure 7.4, the number of wavelengths supported by each link is increased to 16. At low traffic loads i.e. between 0.05 and 0.3, both GA and PSO schemes show similar blocking probability performance. However, when the traffic load increases to a traffic load of between 0.3 and 0.7, PSO performs better than GA1, GA2 and the SP_FF algorithms. Again, as the links saturate in terms of wavelength availability because of already deployed lightpaths over them (i.e. when the traffic load is above 0.7), the PSO scheme shows comparable connection blocking probability performance to the others. Similar blocking probability performance behaviour can be observed in Figure 7.5 and 7.6, which show the blocking probability versus traffic load for 8 and 16 wavelength based variants of EON network respectively.

Figure 7.3 and 7.5 also shows that PSO performs better in terms of blocking probability performance for EON (figure 5.4) network as compared to NSFNET (figure 4.2) network. EON network is a 20 node network with higher average nodal degree as compared to NSFNET (14 node network). Therefore, in the case of EON, PSO algorithm will find more alternative routes during dynamic RWA computation which results in better performance. However, more options for route selection means more computational time required to solve routing sub-problem which increases connection setup time.

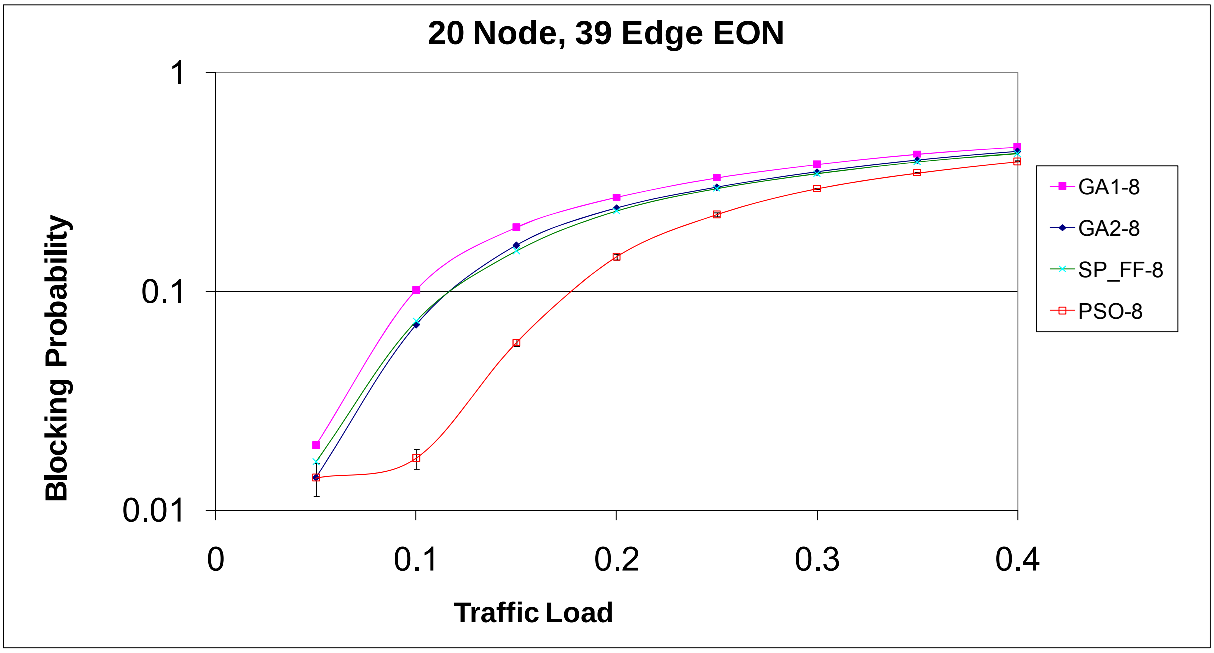


**Figure 7.5: Blocking Probability Versus Traffic load between PSO, GA1, GA2 and SP_FF algorithms for EON (Figure 5.4). Number of Wavelengths = 8, α = 0.9, Confidence Interval = 95%, Population size (for both GA and PSO algorithms) = 15, Iterations (PSO)/particle = 20, Generations (GA) = 20.**

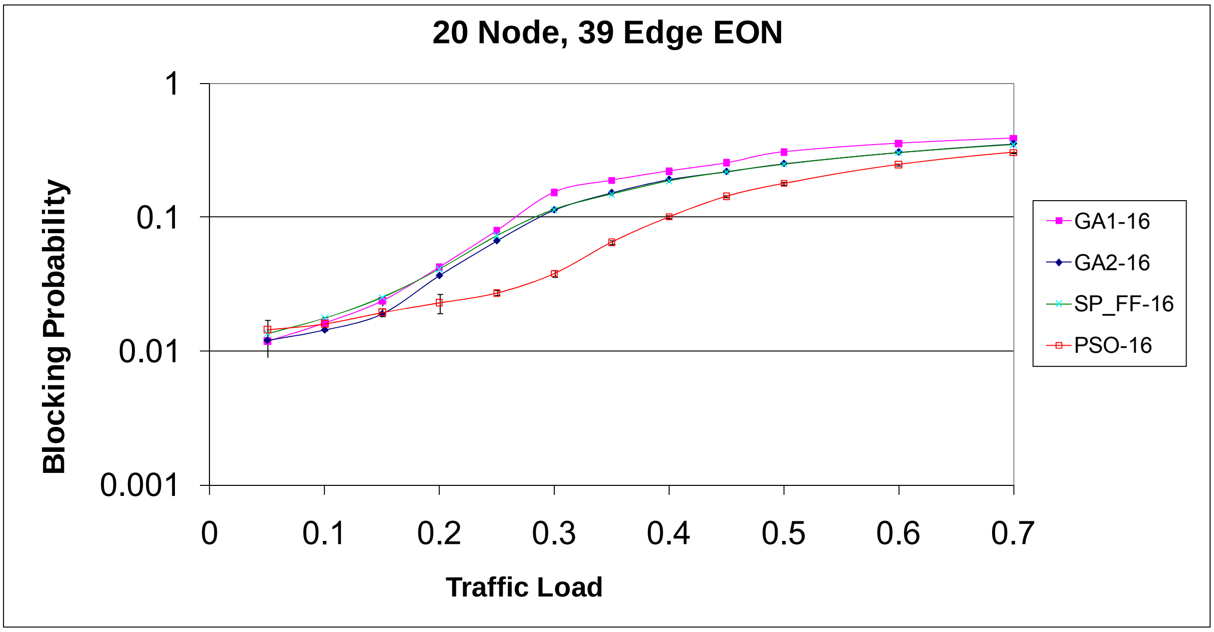


**Figure 7.6: Blocking Probability Versus Traffic load between PSO, GA1, GA2 and SP_FF algorithms for EON (Figure 5.4). Number of Wavelengths = 16, α = 0.9, Confidence Interval = 95%, Population size (for both GA and PSO algorithms) = 15, Iterations/particles (PSO) = 20, Generations (GA) = 20.**

### 7.5.3. Effect of ‘α’ on Blocking Probability performance

In the proposed fitness function given by equation 7.5, the value of ‘α’ is used to control the influence of the path length and the number of free wavelengths available. Generally, the number of free wavelengths and route length (number of hops) are correlated as routes having less free wavelengths tend to be shorter routes. Therefore, choosing a route with more free wavelengths gives better blocking probability performance. However, it is observed from the experiments that at very low traffic loads when most of the wavelengths are free, choosing the shortest route instead of routes having large number of free wavelengths gives better performance. At very low network loads, if preference is given to those routes having more free wavelengths available, there’s a chance that it can also lead to longer routes selected as most of the wavelengths are free at that time. Gradually the availability of free wavelengths on the routes will decrease with connection provisioning. At the later stage this can led to an increase in the blocking probability for future connection requests.

Therefore it would appear that there is a need to dynamically control the ‘α’ factor that can give more weight to hop-length factor when the network load is low and give more weight to ‘number of free wavelengths’ factor at moderate and high traffic loads. In the proposed fitness function, both factors (route length and number of free available wavelengths) are normalized. The advantage of using such a fitness function is that it decreases the variation of mean blocking probability for different values of ‘α’. This removes the need to dynamically adjust the ‘α’ factor.

The blocking probability performance of the proposed ‘normalized fitness function’ given by Equation (7.5), is carried out for different values of ‘α’ in Figure 7.7. Comparison is made with respect to SP_FF scheme.

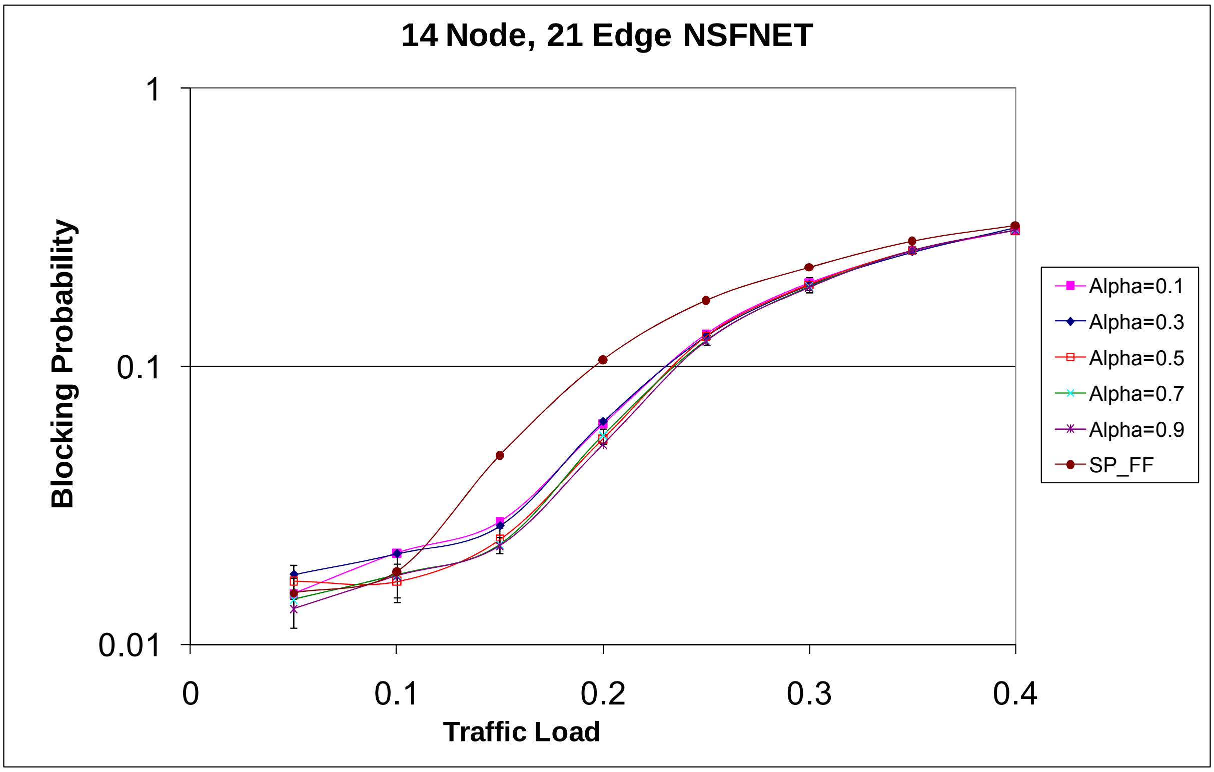


**Figure 7.7: Blocking Probability Versus Traffic load between different values of 'α' for PSO using proposed fitness function given by Equation (7.5) with SP_FF algorithms for NSFNET (Figure 4.2). Number of Wavelengths = 8, Population size = 15, Iterations (PSO) = 20.**

In Figure 7.8, the same experiment is carried out using a traditionally normalized fitness function $F_N(i)$, as given by Equation (7.8). The main difference between $F(i)$ and $F_N(i)$ is that the proposed fitness function $F(i)$ given by equation 7.5 makes sure that when most of wavelengths in the network are free, the routes having a shorter path are given preference.

$$F_{NN}(i) = \left[ \alpha * \frac{(L_{\max} - L_{sd})}{L_{\max}} \right] + \left[ (1-\alpha) * \left( \frac{W_{sd}}{W_{Total}} \right) \right] \qquad \text{Equation (7.8)}$$

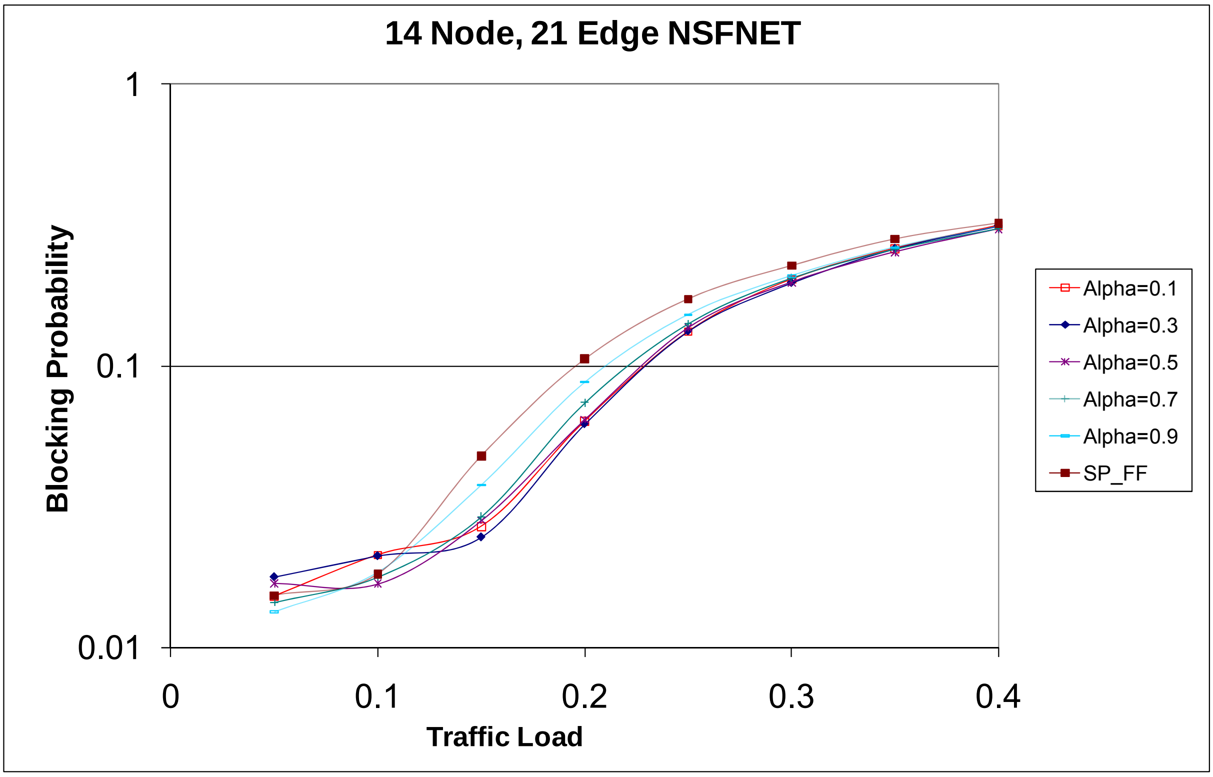


**Figure 7.8: Blocking Probability Versus Traffic load between different values of 'α' for PSO using non-normalized fitness function given by Equation (7.8) with SP_FF algorithms for NSFNET (figure 4.2). Number of Wavelengths = 8, Population size = 15, Iterations (PSO) = 20.**

Figure 7.7 and 7.8 clearly show that using the proposed normalized fitness function, the need to dynamically adjust the algorithmic parameter 'α' is reduced as compared to the non-normalized fitness function case where altering α is seen to have a notable impact on the blocking probability performance. To evaluate the blocking probability performance between PSO and Genetic algorithm (GA) for a different fitness function, an experiment is conducted (shown in figure 7.9) where the fitness function used for both PSO and GA is based on number of hops in the route given by Equation 7.9.

$$F_{spr} = 1.0 / \mathit{Number\ of\ hops} \qquad \text{Equation (7.9)}$$

In this case, the same implementation of Genetic algorithm proposed in [110] is used but with a different fitness function giving by equation 7.9. Figure 7.9 shows that for this fitness function, PSO performs better in terms of blocking probability as compared to the genetic algorithm.

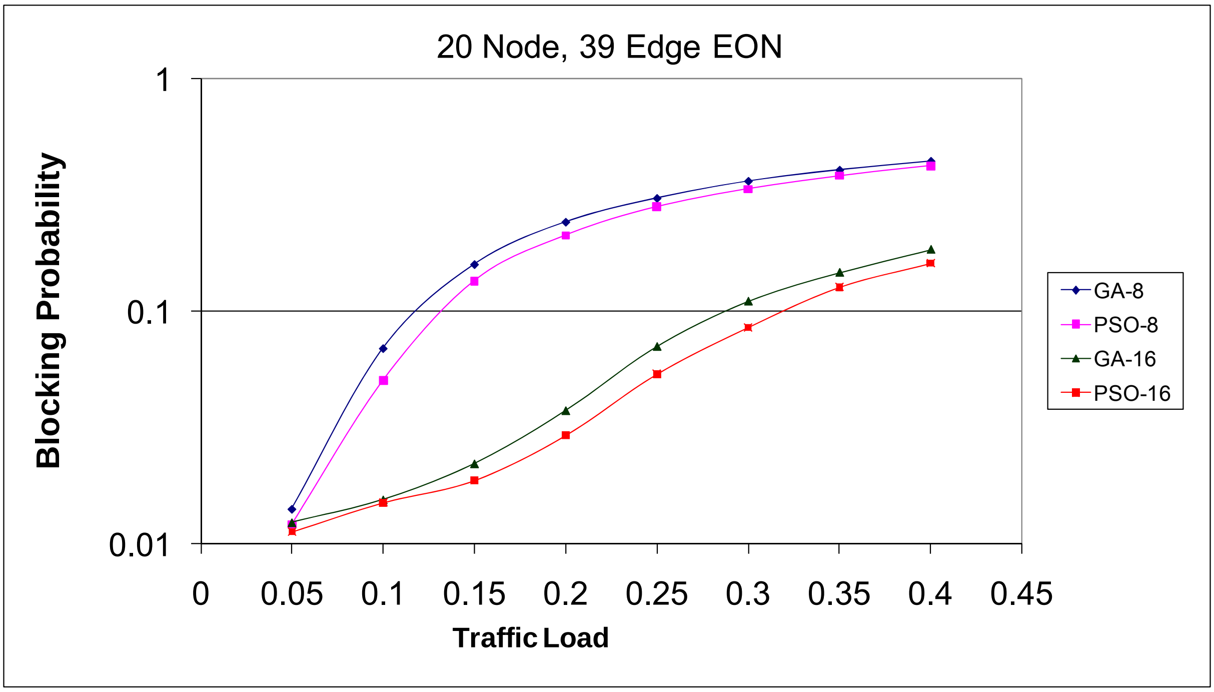


**Figure 7.9: Blocking Probability Versus Traffic load between PSO and GA using fitness function given in Equation (7.9) for EON (Figure 5.4). Number of wavelengths supported is 8 and 16 respectively. Population size (Both PSO and GA) = 10, Iterations (PSO) = 10, Generations (GA) = 10.**

### 7.5.4. Connection Provisioning Time

Connection provisioning time is an important criterion when evaluating the network performance and efficiency of the underlying algorithms used to perform the computation. From both network provider's and customer's point of view a minimal connection provisioning time is desired. In order to setup a connection (lightpath) in WDM optical networks, two major time-consuming tasks are: Firstly is the computation time required to solve dynamic RWA problem i.e. route computation time. Secondly is the actual lightpath setup time required by the control plane of the network in order to instruct each intermediate node to configure the physical hardware appropriately.

In Table 7.1, a comparison is carried out for route computation times and the respective blocking probabilities between the PSO scheme and the Genetic algorithm (GA). For evaluation fairness between the blocking probability performance and route computation times of PSO and GA, the same implementation of GA proposed in [110] is used but both PSO and GA in this case use the proposed fitness function in Equation 7.5. The experiment is repeated at a network load of 0.2 for different population sizes. In each experiment, the population size i.e. number of particles (PSO) and number of chromosomes (GA) are kept the same.

Table 7.1 clearly shows that for different population sizes and number of evolutionary iterations, the proposed PSO scheme shows a better connection blocking probability as compared to GA. It also shows that the PSO scheme shows significantly better performance in terms of route computation times. In genetic algorithms, members of the population perform special operations like reproduction, mutation and selection procedure for inclusion in the next generation. These special operations significantly add to the cost in terms of computational complexity. Another factor is the large number of fitness function evaluations required for each chromosome in GA as compared to number of fitness function evaluations required by each particle in PSO. The simulation is carried out on a Dell optiplex GX520 machine having 3.00 GHz processor and 2 GB of RAM in windows environment.

**Table 7.1: Comparison of blocking probability and route computation time (milliseconds) between proposed PSO-based scheme and GA [110] using proposed fitness function (Equation 5.5) for EON (figure 5.4), having different population sizes and iterations/generations. Number of wavelengths = 8, α = 0.9, Network Load = 0.2, NP = Number of particles (PSO), NI = Number of iterations (PSO), P = Population size (GA), G = Generations (GA).**

| Serial # | P (GA) | G (GA) | NP (PSO) | NI (PSO) | Blocking Probability | Route Computation time (ms) |
|---|---|---|---|---|---|---|
| 1) | 5 | 5 | - | - | 0.26584 | 9.7 |
| | - | - | 5 | 5 | 0.17470 | 3.4 |
| 2) | 5 | 10 | - | - | 0.25990 | 18.1 |
| | - | - | 5 | 10 | 0.13856 | 6.2 |
| 3) | 5 | 15 | - | - | 0.25689 | 25.3 |
| | - | - | 5 | 15 | 0.12275 | 8.7 |
| 4) | 10 | 5 | - | - | 0.20328 | 26.7 |
| | - | - | 10 | 5 | 0.12944 | 6.7 |
| 5) | 10 | 10 | - | - | 0.20152 | 48.3 |
| | - | - | 10 | 10 | 0.11777 | 12.1 |
| 6) | 10 | 15 | - | - | 0.19962 | 64.4 |
| | - | - | 10 | 15 | 0.10595 | 17.4 |
| 7) | 15 | 5 | - | - | 0.19805 | 59.0 |
| | - | - | 15 | 5 | 0.11724 | 9.8 |
| 8) | 15 | 10 | - | - | 0.19457 | 117.4 |
| | - | - | 15 | 10 | 0.10657 | 19.2 |
| 9) | 15 | 15 | - | - | 0.19369 | 158.1 |
| | - | - | 15 | 15 | 0.10484 | 30.32 |

## 7.6. Summary

The particle swarm optimization (PSO) based scheme proposed in this chapter, effectively solves the dynamic routing and wavelength assignment problem for wavelength continuous WDM optical networks without wavelength conversion capability. The proposed fitness function given in equation 7.5, takes into account the normalized path length and the normalized number of free wavelengths available during the route evaluation.

The simulation results show that the PSO algorithm performs better in terms of blocking probability as compared to the Genetic Algorithms proposed in [108], [110] and a Shortest Path – First Fit heuristic algorithm. The normalization of 'path length' and the 'number of free wavelengths' effectively reduces need to have dynamic controlling factor 'α'. The proposed scheme also performs significantly better in terms of route computation time relative to GA. The simulation results presented in this chapter also show that the PSO scheme performs significantly better as compared to other heuristic algorithms like ACO, SP-FF, SP-MU and SP-MU (sorted) for provisioning lightpath connections in case of incremental traffic. PSO can successfully provision a significantly larger number of connection requests as compared to algorithms like ACO, SP-FF, SP-MU and SP-MU (sorted).

During GA's reproduction stage, the selection operator eliminates those members of the population which have a poor fitness value from being included in the next generation. Regardless the selection method used, the chromosome with the best fitness value is always moved to the next generation. This strategy is called *elitist* strategy [120]. However the PSO is the only evolutionary algorithm that doesn't incorporate survival of the fittest through operations like selection [81]. So there is always a chance that a member of population that has a poor initial fitness value, might evolve over time through self-exploration of the search space and by 'exploiting' the exploration of the best member in the neighbourhood, to become the best member of the population. As compared to ACO, PSO doesn't need to maintain and update pheromone tables at intermediate nodes.

The proposed PSO algorithm employed for solving dynamic RWA problem, performs better both in terms of connection blocking probability and execution time as compared to ACO [96] and GAs [108, 110]. For all these reasons, the proposed particle swarm optimization (PSO) based scheme along with the proposed fitness function is a suitable candidate for connection provisioning in wavelength continuous WDM networks without any wavelength conversion capability.

# CHAPTER 8 CHAOTIC PSO (CPSO) BASED DYNAMIC ROUTING AND WAVELENGTH ASSIGNMENT

The superior blocking probability performance of particle swarm optimization as compared to other heuristic schemes like Genetic Algorithms and Ant Colony Optimization etc makes it a suitable candidate for connection provisioning in Next Generation Optical Networks (NGONs). The ability of the PSO algorithm to search and converge toward an optimal/near-optimal solution depends on the number of particles being used in the swarm for searching problem search space. The more particles being used for searching problem domain, the more will be the chances of finding optimal solution to the problem being addressed. However, increasing the number of particles also increases the computational complexity and thus execution time of the algorithm. In case of NP-hard problems relating to dynamic environments like dynamic RWA, it is desirable for any heuristic algorithm to provide a solution within a given amount of time. For the PSO algorithm, computational complexity and execution time can be controlled simply by adjusting number of particles in the swarm or by limiting the number of iterations allowed for each particle. Therefore, it is an important performance feature of the PSO algorithm to provide a good quality solution while solving the dynamic RWA problem, even for a fewer number of particles in the swarm or when the swarm is constrained to fewer iterations.

In this chapter, a novel Chaotic Particle Swarm Optimization (CPSO) based scheme is proposed for solving Dynamic Routing and Wavelength Assignment problem in All-Optical WDM optical networks without any wavelength conversion. As compared to PSO algorithm proposed in the previous chapter (Chapter 7), the difference here is the introduction of a chaotic factor during the velocity computation. The chaotic factor introduces slight randomness in the particle's search. This helps the particles avoid being trapped in local optima and therefore to converge quickly towards an optimal/near-optimal solution. The proposed fitness function improves the connection blocking probability by taking into account the normalized path length and wavelength availability over the whole path. Simulation results show that CPSO performs better as compared to PSO in terms of blocking probability performance even for a few particles in the swarm and also as compared to other heuristic schemes.

## 8.1. Generalized Particle Swarm Optimization (PSO)

PSO is population based scheme where a swarm is a collection of population members called 'particles' which evolves over time for problem solving. Each particle in the swarm has both a position and velocity. The position of the particle in multidimensional problem space represents a candidate solution. The velocity of the particle moves it from one position to another position over the problem search space. In order to avoid the velocity from becoming very large in the initial PSO iteration, and to avoid premature convergence to a local optima, a number of improvements are suggested in the literature [115, 116 and 117]. For example, Clerc [63] proposed the use of constriction factor '$\chi$' in order to prevent large velocity values. The PSO equation where the position and velocity represents physical attributes of the particles is represented by (8.1) and (8.3).

Calculating a Single Particle's New Velocity

$$V_{id} = \chi[V_{id} + \eta_1 r_1 (P_{id} - X_{id}) + \eta_2 r_2 (P_{id}^n - X_{id})]$$
$$where \quad i = 1,2,...N.\ d = 1,2,...D \tag{8.1}$$

Where,

$$\chi = 2 * \left( \left| 2 - \eta - \sqrt{\eta^2 - 4\eta} \right| \right)^{-1} \quad if\ \eta = \eta_1 + \eta_2 > 4 \tag{8.2}$$

"Moving" a Single Particle in a Swarm

$$X_{id} = X_{id} + V_{id} \tag{8.3}$$

In Equation 8.1 and 8.3,

$P_{id}$ is the personal best position, a particle has reached;

$P_{id}^n$ is the global best position of all the particles.

'$\eta_1$' (the self-confidence factor) and '$\eta_2$' (the swarm-confidence factor) are positive constants called '*acceleration constants'* to determine the influence of $P_{id}$ and $P_{id}^n$.

'$r_1$' and '$r_2$' are independent random numbers in the range [0, 1].

‘N’ is the total number of particles in the swarm.
‘D’ is the dimension of the problem search space i.e. the number of functional parameters being optimized.

PSO starts by randomly initializing the position and velocities of all the particles in the swarm over the problem space. The position of $i^{th}$ particle is represented by the vector $X_i = [X_{i1}, X_{i2} \dots X_{iD}]$ and velocity of $i^{th}$ particle is represented by the vector $V_i = [V_{i1}, V_{i2} \dots V_{iD}]$. For each iteration (until the convergence criteria is met), the fitness function is applied to the particles to quantize their respective positions over the problem search space. The particle with the best fitness value in the whole swarm is marked as the global. Each particle will also keep a record of its personal best position searched so far. Equation (8.1) is used to calculate new velocity for each particle in the swarm based on particle’s previous velocity, its current and personal best position, and the position of the particle with the best fitness value in the swarm. Equation (8.3) is then used to apply the velocity to the particle. As a result of this, the particle will move to a new position i.e. it will now represent a new candidate solution to the problem being studied.

## 8.2. Chaotic Particle Swarm Optimization (CPSO)

One problem with PSO is the problem of being trapped in local optima which can lead to premature convergence of the swarm members. Recently, many studies have been presented to improve the performance of PSO based on chaotic search behaviour. To improve the performance of PSO, [121] has proposed a hybrid PSO based scheme by incorporating chaos. The chaotic factor here represents randomness induced during particle’s position updating as shown in equation 8.4 and 8.5. Simulation results for this hybrid scheme show that the chaos greatly improves the searching efficiency and searching quality of the swarm. Similarly, in [122] and [123], chaos mapping has been introduced to enhance the performance of PSO algorithms for reactor power optimization and short term hydroelectric system scheduling respectively. A chaotic PSO algorithm is proposed in [124] for image classification. The biological ‘atmosphere’ for the position updates of the particles is modelled by introducing wind-speed and wind-direction along the flight-path of the particles, which incorporates chaos theory in PSO [124]. Introduction of wind-speed to particle’s position update, influences the motion of the swarm members by either assisting them (if the wind direction is along the flight-path) or opposing them (if the wind direction is against the flight-path) in reaching the global best particle of the swarm.

## 8.3. Proposed CPSO based scheme for dynamic RWA

In this chapter, a novel chaotic particle swarm optimization (CPSO) algorithm, exploiting the concept of a chaos factor in PSO [124], is proposed for dynamic routing and wavelength assignment in All-Optical WDM networks without any wavelength conversion capability. Equation (8.4) is used to calculate the new position of the particle instead of (8.3) in the case of CPSO. Three factors involved in position update are: the particle's previous position, its new velocity calculated according to (8.1) and the chaos factor calculated according to (8.5).

$$X_{id} = X_{id} + V_{id} + \varphi_c \tag{8.4}$$

where,

$$\varphi_c = \varphi_c + v_{op} * rnd_1 + v_{fa} * rnd_2 \tag{8.5}$$

$V_{op}$ = - 1 and represents the chaos factor opposing the movement of swarm particles.
$V_{fa}$ = +1 and represents the chaos factor favouring the movement of the swarm particles.
$rnd_1$ and $rnd_2$ are independent random number in the range [0,1].
$\varphi_c$ is the favourable or unfavourable chaos factor, resulting in either slowing down or speeding up the particle over the search space.

Since each particle in the swarm typically searches the problem space spatially separated, in different directions, so different particles will experience different conditions based upon an opposing or favourable chaos factor. Therefore, each particle's position is updated by the chaos-factor equation separately. In [124], when both the opposing and favourable chaos-factors are equal, it models non-chaotic PSO swarm.

### 8.3.1. Encoding and Decoding of Particles in the Swarm

A typical encoding scheme for path representation is the 'direct-representation' scheme where a path is represented as a sequence of node identification numbers from the source node to the destination node. Encoding schemes based on direct representation have been used to encode paths in [111]. Gen et al. [112] proposed an indirect-representation scheme (priority-based encoding) for solving the shortest path problem using genetic algorithms. In the priority-based encoding scheme, a path (chromosome) is represented by encoding some guiding information about a node instead of the node-ID. An example of such guiding information can be the node priority. This guiding information is used to generate a path from an arbitrary chromosome. In [113] a 'weighted encoding scheme' is used for chromosome representation in GA, whereas in [109], a cost-priority based encoding scheme is used for representing a particle in PSO.

In the proposed CPSO algorithm, for simplicity, a priority based encoding scheme is used. The position of the particle is represented as a vector of node priorities. The path, which a particle represents, is decoded using a path growth procedure [112] by starting from the source node and then sequentially appending the intermediate nodes one-by-one, till the destination node is reached. During the path growth procedure, if more than one node is available, the node with the highest node priority is selected. Every time as node is selected during path construction, it is marked as unavailable for the rest of path growth procedure. Figure 8.1 illustrates an example of priority based encoding, where a path is being constructed for a lightpath request between source node '1' and destination node '9' in NSFNET (previously shown in figure 4.2) by decoding the position of the particle using the 'path growth' procedure.

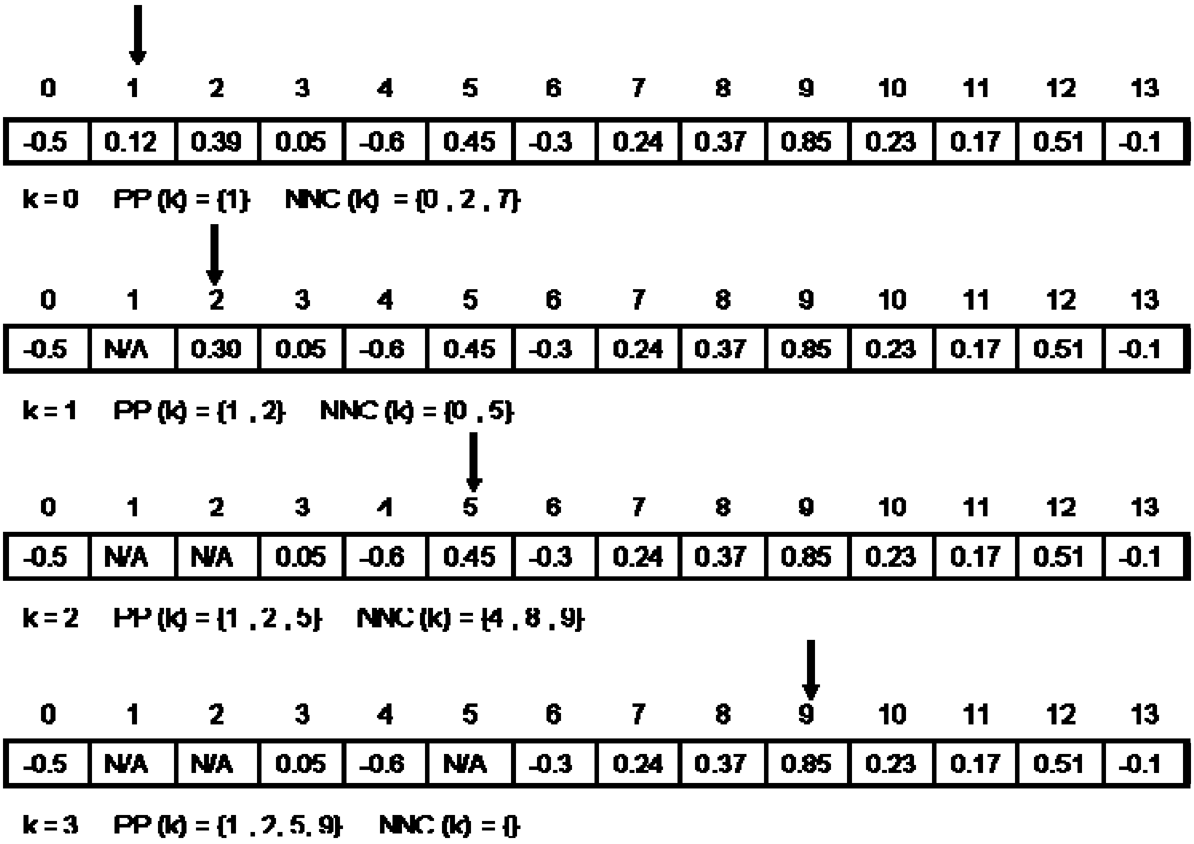


**Figure 8.1: Priority based encoding and Path growth procedure for decoding. k = iteration number. PP (k) is the 'partial path vector' at iteration 'k'. NNC (k) is the 'next node candidate' vector.**

### 8.3.2. Fitness Function

With CPSO, a novel fitness function is used which takes into account not only the length of the route i.e. number of hops between the source and destination node. It also considers the normalized number of free wavelengths available over the whole route while satisfying wavelength continuity constraint. The fitness function used with CPSO for solving dynamic RWA problem is represented by Equation (8.6).

$$F(i)=\begin{cases}\left[\alpha*\dfrac{(L_{\max}-L_{sd})}{L_{\max}}\right]+\left[(1-\alpha)*\left(1-\dfrac{W_{Total}-W_{sd}}{W_{Total}}\right)\right] & if\ W_{sd}>0\ \&\ W_{sd}<W_{Total}\\ \left[\alpha*\dfrac{(L_{\max}-L_{sd})}{L_{\max}}\right]+\left[(1-\alpha)\right] & if\ W_{sd}=W_{Total}\\ -100.0 & if\ W_{sd}=0\end{cases} \tag{8.6}$$

$L_{max}$ is the maximum length of the route between any source – destination pair
$L_{sd}$ is the length of the route between source 's' and destination 'd'.
α [0, 1] is a design parameter
$W_{Total}$ is the total number of wavelengths supported by the optical network
$W_{sd}$ then defines the number of free wavelengths available over the route between source 's' and destination 'd'.

## 8.4. Simulation Results and Analysis

In this section, the connection blocking probability performance of the proposed Chaotic Particle Swarm Optimization based scheme (hereafter simply referred as the CPSO algorithm) for solving dynamic RWA problem is evaluated. A simulator has been implemented in Opnet Modeler™ [118]. 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 [103.]. Each simulation is carried out 15 times and the averages are reported here. Experiments are conducted for 16 node NSFNET (figure 5.5), 14 node NSFNET (figure 4.2) and 20 node EON (figure 5.4) networks, where all WDM links are either assumed to have a capacity of 8 and 16 wavelengths, as indicated.

A performance comparison of the solution quality for a fitness function given by equation 8.6, with different swarm sizes is carried out between Particle Swarm Optimization (hereafter simply referred as PSO algorithm) and CPSO algorithm. Both for PSO and CPSO, a global neighbourhood is assumed where all the members in the swarm are the particle's neighbours. During initialization, each particle's position (node priorities) and velocity are randomly initialized with real numbers in the range [-1.0, 1.0]. In CPSO, the initial chaos-factor is assumed to be 0.0. All the network conditions and other algorithmic parameters are kept the same for both PSO and CPSO. A shortest path routing algorithm with first-fit wavelength assignment algorithm (SP-FF) algorithm and Ant Colony Optimization (ACO [96]) are used to gauge the performance of PSO and CPSO.

The connections are added incrementally where each connection stays in the network for infinite connection holding time. The moment the first connection request is blocked due to unavailability of resources, the simulation is stopped and the number of connections provisioned so far is counted. The source node and destination nodes are chosen randomly having uniform distribution. As shown in figure 8.2, for different numbers of particles in the swarm, CPSO always performs better than PSO especially when there are only a few particles. Also with just 2 particles in the swarm, CPSO performs significantly better as compared to SP-FF and ACO algorithm in terms of number of connections that can be provisioned for a given number of wavelengths (80 in this case) supported by optical fibres in the network. It is also evident from the figure 8.2 that after a certain point, increasing the number of particles in the swarm does not increase the performance of CPSO or PSO algorithms significantly, but only increases the computational complexity of the algorithm.

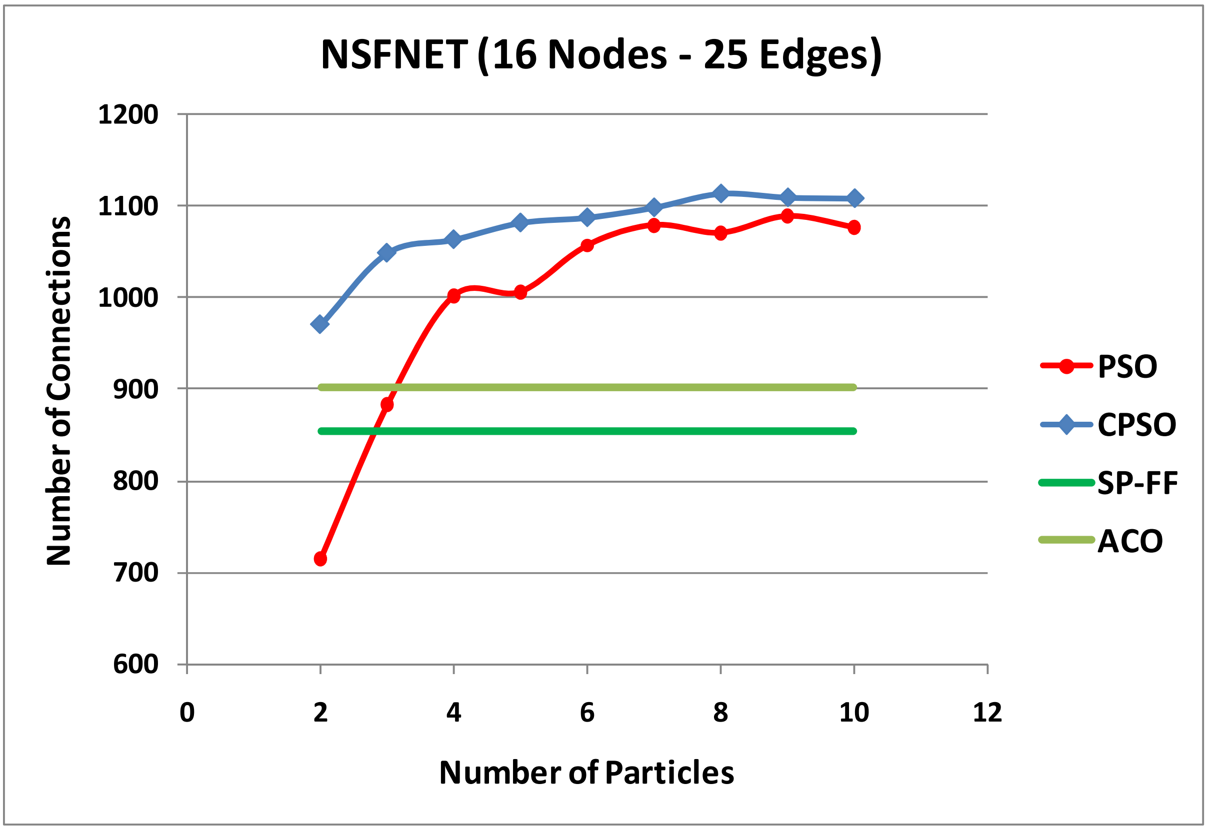


**Figure 8.2: Performance comparison between PSO, CPSO, ACO and SP-FF algorithm in case of incremental traffic. For PSO and CPSO fitness function given by equation 8.6 is used. NSFNET16 (16 NODE, 25 EDGES) Number of particles = Variable, Iterations Allowed per particle = 10, 'alpha' = 0.5; Number of wavelength = 80.**

For the simulations with dynamic (non-incremental) traffic, where a connection request arrives randomly on the fly-randomly and stays in the network for a finite amount of time, a traffic model is used where connection requests are generated at each node following a Poisson process with an arrival rate of $\lambda_{nodes}$. Destination nodes for the connections are randomly chosen according to a uniform distribution. Therefore, the total connection arrival rate ($\lambda_{total}$) in the whole network is the product of total number of nodes in the network and $\lambda_{nodes}$.

If φ is the total number nodes in the network, then

$$\lambda_{total} = \varphi * \lambda_{nodes} \tag{8.7}$$

The connection holding time is exponentially distributed with mean 'T' seconds. Therefore, traffic load is given by Equation (8.8).

$$Traffic\ Load = \lambda_{total} * T \Big/ \varphi * (\varphi - 1) \tag{8.8}$$

For the experiments, the value of 'T' is kept constant at 50 seconds and the value of $\lambda_{nodes}$ is changed in order to vary the value of normalized traffic load. A distributed control system is used where each node in the network upon the arrival of a connection request arrival performs a dynamic routing and wavelength assignment computation (using out-of-band signalling). For the wavelength assignment, DIR (destination-initiated reservation) [119] along with a first-fit algorithm is used. Each node is assumed to have wavelength usage information of the whole network. No alternative routing is used and no re-attempts are made for route re-computation once a connection is blocked.

In order to evaluate the performance of PSO and CPSO in terms of solution quality, an experiment is carried out where both schemes use the fitness function shown in (8.7) with an objective of finding the shortest route between source-destination node.

$$F_{spr} = 1.0 \Big/ Number\ \ of\ \ hops \tag{8.7}$$

Success ratio of an algorithm is defined as (average) number of times an algorithm finds global optimum i.e. shortest route for a connection, divided by total number of connection requests. Figure 8.3 shows that for a variable number of particles in the swarm, CPSO performs better than PSO in terms of success in finding shortest route. The number of iterations per particle is kept constant for both PSO and CPSO. Figure 8.4 show that even when various iterations per particles is allowed, CPSO continues to perform better than the PSO scheme. The number of particles in this case is kept constant at 8.

Figure 8.3 and 8.4 clearly show that when swarm size or number of iterations allowed for each particle, are altered, the proposed CPSO scheme presents a significantly better solution as compared to the PSO scheme. The main reason for the better CPSO performance is its ability to avoid local optima solutions and quick convergence towards a optimal/near-optimal solution as compared to PSO algorithm.

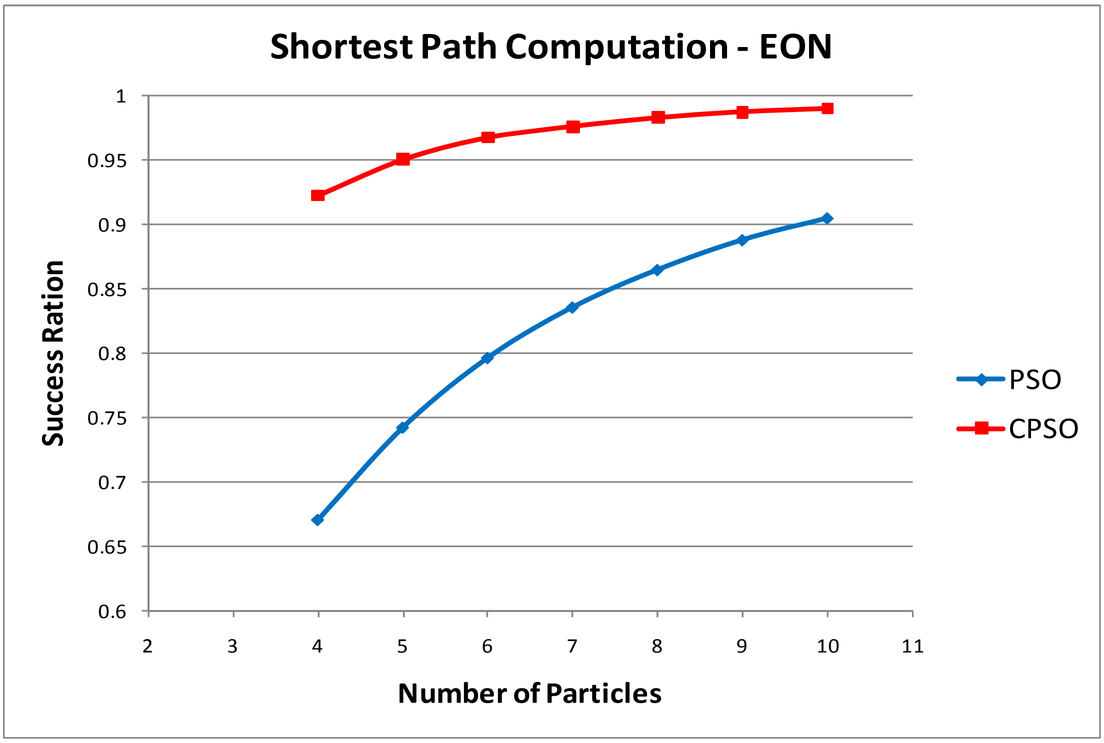


**Figure 8.3: Success ratio in finding shortest route versus Number of particles in the swarm for PSO and CPSO in EON-network (shown in figure 5.4). Number of iterations allowed per particle = 10. Network Load = 0.2.**

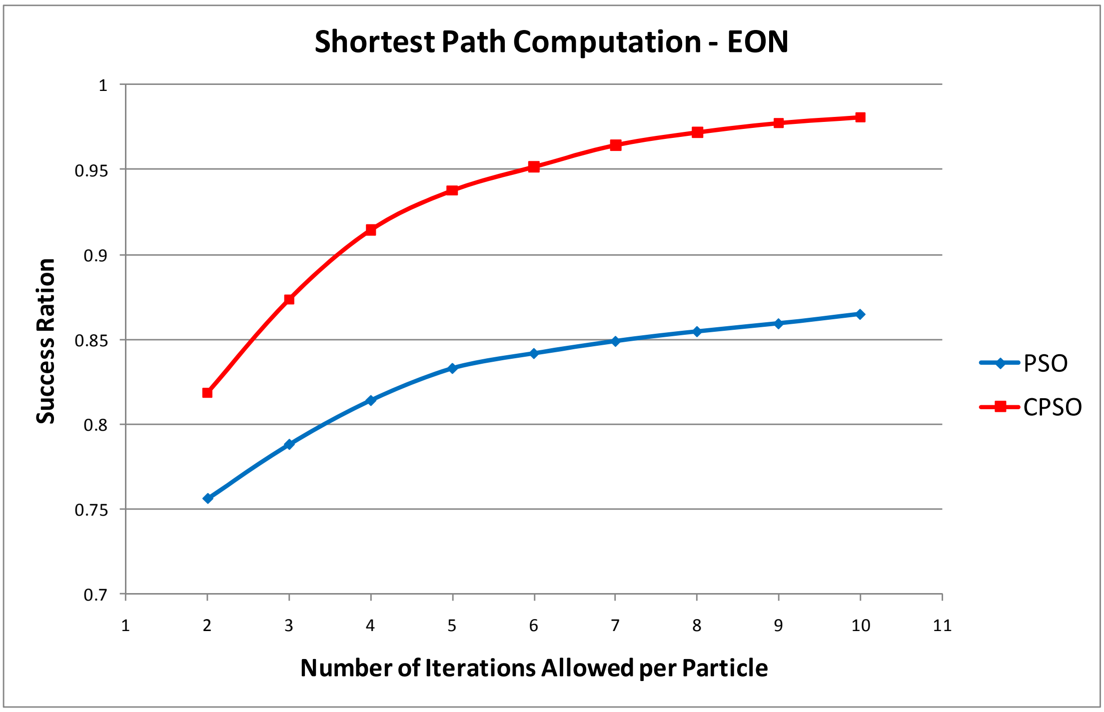


**Figure 8.4: Success ratio in finding shortest route versus Number of iterations per particle allowed for PSO and CPSO in EON-network (shown in figure 5.4). Number of particles in the swarm = 8. Normalized Network Load = 0.2.**

In order to evaluate the performance comparison between PSO and CPSO in terms of blocking probability performance at different networks loads, a set of simulations are carried out. An 8-wavelength variant of NSFNET (figure 4.2) and EON (figure 5.4) are used. Both PSO and CPSO are subjected to the same network conditions and algorithmic parameters, like the number of particles in the swarm, number of iterations allowed per particle, 'α', connection holding time etc. Figure 8.5 and 8.6 clearly show that as compared to SP-FF algorithm, PSO and CPSO perform significantly better. At low networks loads, both PSO and CPSO performs more or less similarly in terms of blocking probability performance for future connection requests. However, when the normalized network load is increased i.e. above 0.25 in NSFNET (figure 8.5) and above 0.2 in the case of EON network (figure 8.6), CPSO performs better as compared to PSO. The main reason of better performance of CPSO is due to its ability to avoid local optima as compared to PSO algorithm for solving dynamic RWA problem.

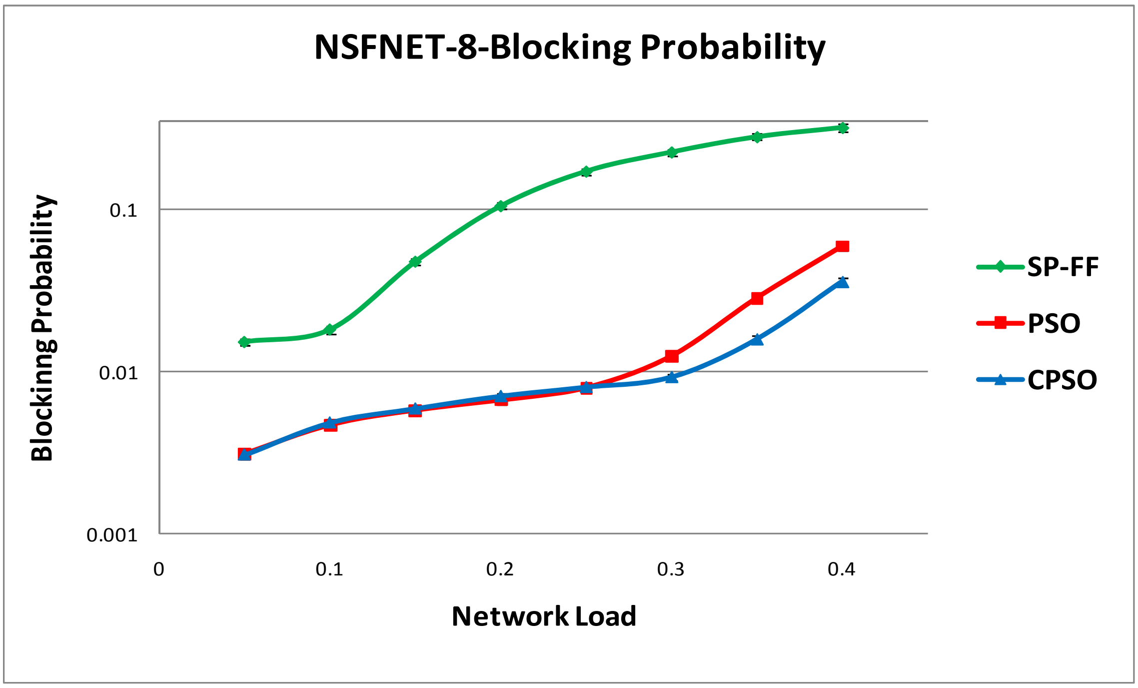


**Figure 8.5: Blocking Probability Performance comparison between PSO and CPSO for different network loads. Number of iterations per particle allowed = 8. Number of particles in the swarm = 6. 'α' = 0.5, Connection Holding Time = 50.0. NSFNET figure 4.2) is used.**

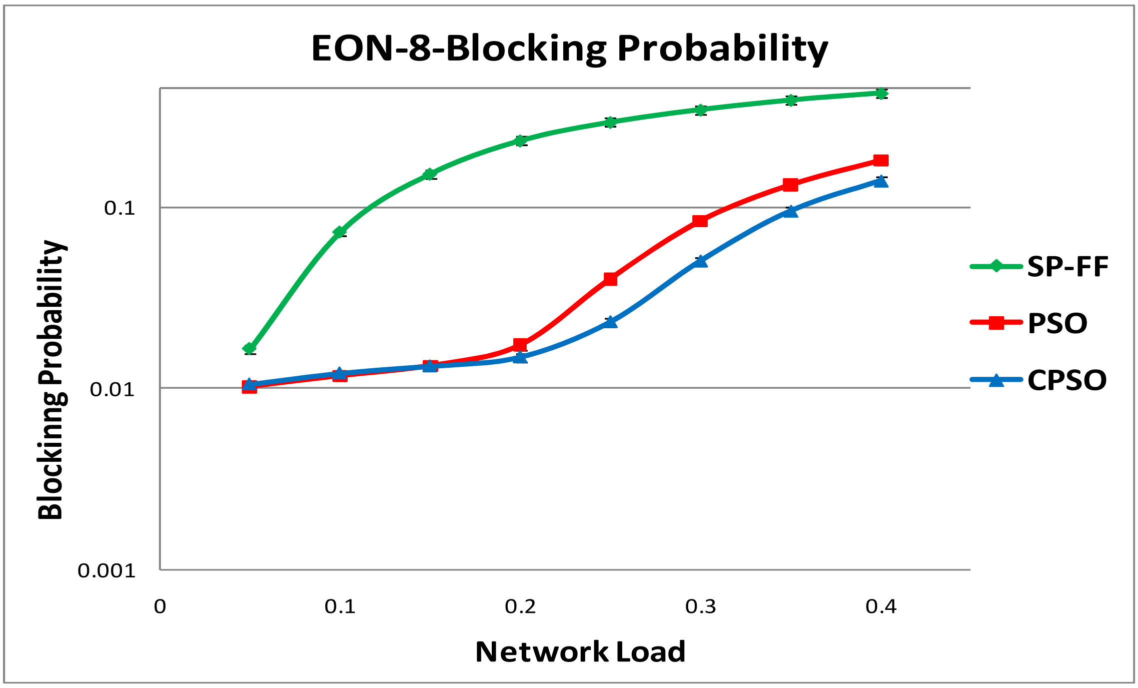


**Figure 8.6: Blocking Probability Performance comparison between PSO and CPSO for different network loads. Number of iterations per particle allowed = 8. Number of particles in the swarm = 6. 'α' = 0.5, Connection Holding Time = 50.0. EON-network (shown in figure 5.4) is used.**

## 8.5. Summary

The proposed Chaotic Particle Swarm Optimization (CPSO) based scheme effectively solves dynamic RWA problem for WDM optical networks without wavelength conversion. A novel chaotic factor is introduced into the PSO algorithm which induces slight randomness in the search behaviour of the particles. This chaotic factor helps the particles not only avoid locally optimal solutions, but it also helps the swarm particles to quickly converge towards an optimal/near-optimal solution.

Simulation results show that CPSO performs better as a connection provisioning algorithm not just as compared to heuristic algorithms like ACO proposed in [96] and the SP_FF algorithm, but also the PSO algorithm. CPSO's ability of relatively quickly converge towards optimal/near-optimal solution as compared to PSO algorithm significantly improves its ability to provision more connections successfully, for a given number of wavelengths. CPSO also provides a better quality solution as compared to PSO for a simpler fitness function with an objective of finding shortest route between source and destination nodes when different number of particles in the swarm and different number of iterations for each particle are allowed. For non-incremental (dynamic, on-the-fly) low traffic loads, CPSO algorithm performs similarly to the PSO algorithm. However, as the network load is increased to moderate or high traffic loads, CPSO show better results in terms of blocking probability performance.

For these reasons, the CPSO scheme with the proposed fitness function is a suitable candidate for connection provisioning in All-Optical WDM networks.

# CHAPTER 9 DISCUSSION

## 9.1. Review of Thesis

With the growth of video and high-speed packet-based business services such as Ethernet private line/LAN, grid computing, access network provider backhaul and storage area networking, the value of customer-centric on-demand channel provisioning is receiving attention. Furthermore, the flexibility of an ASON infrastructure enables network operators to establish and release wavelength paths without human intervention. This ability offers several cost benefits. Firstly, it eliminates stranded capacity by allowing resources to be redirected to match evolving bandwidth requirements without re-engineering the network. Bandwidth requirements over the lifetime of the network can deviate substantially from original forecasts. Secondly, it reduces the need for network planning, thereby reducing the upfront cost of deploying a network. The ability to reallocate capacity after a network has been deployed simplifies planning for bandwidth growth and so allows operators to reduce the amount of extra capacity needed to guarantee service delivery to their customers arising from faults or other disruptions.

All-optical WDM networking is a promising technology for long-haul backbone and large metropolitan optical networks in order to meet the non-diminishing bandwidth demands of future applications and services. Today's technological advances in optical networking components like Reconfigurable Optical Add Drop Multiplexer (ROADM) and Optical Cross Connect (OCX) can provide fast and automatic provisioning of optical channels. Connection (lightpath) provisioning in optically switched networks requires both route computation and a single wavelength to be assigned for the lightpath. This is called as Routing and Wavelength Assignment (RWA).

RWA can be classified as static RWA and dynamic RWA. In static RWA, all the connection requests that need to be provisioned are known in advance. A typical objective of static RWA is to minimize the number of wavelengths (or other network resources like number of transceivers) required to provision all the given connection requests. Static RWA is an NP-hard (non-polynomial time hard) optimisation task. Dynamic RWA is even more challenging as connection requests arrive dynamically, on-the-fly and have random connection holding times. Traditionally, global-optimum mathematical search schemes like Integer Linear Programming are used to find an optimal solution for NP-hard problems. However such schemes become unusable for connection provisioning in a dynamic environment, due to the computational complexity and time required to undertake the search. Therefore, different heuristic and stochastic techniques are used to enable dynamic provisioning in optical networks. However, heuristic schemes used for solving NP-hard problems do not guarantee an optimal solution to the problem being addressed.

Particle Swarm Optimization (PSO) is a population based global-optimization scheme that belongs to the class of evolutionary algorithms and mimic the social learning behaviour of species like a flock of birds or a school of fish. Such evolutionary algorithms are based on the notion that simple local interactions often lead to a complex global behaviour. In PSO, swarm consists of a collection of non-sophisticated members called particles, which cooperate with each other to perform complex tasks. Particles continue to move around the problem search space trying to better themselves in comparison with their own performance and that of their neighbours. This process continues until either the whole swarm converges or till the given number of iterations completes. PSO has successfully been used to solve many industrial and engineering optimization problems in the diverse areas. The main advantage of using PSO compared to other heuristic based evolutionary algorithm is its simplicity, possessing few algorithmic parameters, and its computational efficiency.

In Chapter 5, a novel PSO-lb algorithm is proposed for solving static RWA problem in WDM networks under wavelength continuity constraint. The objective function is to minimize the number of wavelengths required to provision given set of connection requests and the Average Path Length (APL) of the chosen routes. In PSO-lb, the movement of a particle over the problem search space is mainly influenced by two factors: (1) the position of the particle having best fitness value in the whole swarm (called the global-best) (2) the position of the particle having best fitness value in the local neighbourhood (called the local-best).

To help guide the particles to reach positions with better fitness values, two strategies, namely St. (1) and St. (2), have been proposed which prioritize the selection of route-ids during the computation of the velocity for each particle. To improve the search capability of the PSO-lb scheme, a special operation, referred to as St. (3), is devised for the global best particle in the swarm that reinitializes the position of the global-best particle. The global-best particle attempts ‘t’ times to find an alternate route from pre-computed k-shortest paths and replace it, only if the 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. Simulation results show that allowing the global-best particle to attempt to reinitialize even a couple of routes in the particle’s current position, significantly improves the overall performance of the PSO based static RWA solver Optimal results presented in Chapter 5 and 6 use a value of four. St. (1) and St. (3) significantly improve the performance of PSO-lb both in terms of the number of wavelengths required and the APL of the chosen routes. St. (2) shows a slight improvement in terms of swarm convergence but not as significantly as St. (1) and St. (3) do alone.

Simulation results show that PSO-lb can achieve optimal/near-optimal solution for static RWA problem (table 5.1), which can be confirmed using theoretical lower bound given by equation 5.4 and 5.5. The simulation results also show that the proposed scheme, where particle movement is guided by St. (1), St. (2) and St. (3), performs better as compared to other heuristic algorithms like ACO, SP-FF, SP-MU and SP-MU (sorted). However, one problem with the PSO-lb algorithm is that when the size of the problem space is increased, by increasing the number of pre-computed k-shortest paths being employed, PSO-lb tends to converge prematurely towards local optima. As a result of this, the quality of the solution provided by PSO-lb deteriorates (as shown in the table 5.1 and 5.2).

To improve the performance of the PSO based static-RWA solver, i.e. PSO-lb, and to help the swarm avoid premature convergence; a scheme is proposed, hereafter referred to as the PSO-pb algorithm. In PSO-pb, during the search of the problem space, each particle keeps a record of the best position it has reached so far.  This position is called personal-best position of the particle. In the proposed PSO-pb scheme, the movement of the swarm is influenced by two factors:

1. The position of the Global-Best particle in the swarm (searched so far)
2. The Personal-Best position of the particle (searched so far)

Simulation results presented in Chapter 6, show that PSO-pb performs better in terms of fitness value compared to PSO-lb by reducing the risk of premature convergence. The swarm fitness value in the case of PSO-lb continues to improve much longer, in terms of iterations, compared to PSO-lb.

In Chapter 7, a PSO algorithm is proposed to solve dynamic RWA problem for All-Optical WDM networks without any wavelength conversion capability. In this dynamic environment, connection requests arrive dynamically and stay in the network for random amount of time. The objective of PSO algorithm is to find an appropriate route and wavelength for the connection request whilst reducing the blocking probability for future connections. The proposed fitness function simultaneously takes into account both the hop-length of the chosen route and number of free wavelengths available over the whole of this route. Simulation results show that the fitness function significantly reduces the need to have dynamically adjustable '$\alpha$' factor, which is used to control the influence of hop-length and number of free wavelengths, within the fitness value calculation.

The simulation results show that the PSO algorithm performs better in terms of blocking probability as compared to the Genetic Algorithms proposed in [108], [110] and a Shortest Path – First Fit heuristic algorithm. The simulation results presented in this Chapter 7 also show that the PSO scheme performs significantly better as compared to other heuristic algorithms like ACO [96], SP-FF, SP-MU and SP-MU (sorted) for provisioning lightpath connections in case of incremental traffic. PSO can successfully provision a significantly larger number of connection requests as compared to algorithms like ACO, SP-FF, SP-MU and SP-MU (sorted). The route computation time is another crucial performance criterion to determine the suitability of any heuristic RWA algorithm for operation within an ASON environment. The time required to provision a connection request is directly influenced by the computation time required by the dynamic RWA solver to compute a route and a wavelength (referred here as the route computation time). The superior blocking probability performance and short route computation time of PSO along with the proposed fitness function make it a suitable candidate for connection provisioning in WDM networks like ASON without any wavelength conversion capability. Indeed, the proposed PSO scheme performs significantly better in terms of route computation time relative to GA algorithms and can solve dynamic RWA problem within fraction of a second (table 7.1).

The ability of the PSO algorithm to search and converge toward an optimal/near-optimal solution depends on the number of particles being used in the swarm for searching problem search space. However, increasing the number of particles also increases the computational complexity and thus execution time of the algorithm. Therefore, it is an important performance feature of the PSO algorithm to provide a good quality solution while solving the dynamic RWA problem, when the swarm is constrained to fewer iterations. A simulation study of PSO algorithm revealed a tendency to exhibit slow convergence towards optimal-near optimal solution, especially when the swarm size or particles in the swarm are constrained to fewer iterations. To improve convergence speed of the algorithm, a novel chaotic factor is introduced (CPSO) which induces slight randomness in the search behaviour of the particles. Simulation results presented in Chapter 8 show that the randomness introduced in CPSO enable the swarm particles to reach optimal/near-optimal solution in significantly fewer iterations relative to a similar scheme without this factor present.

## 9.2. Future Work

In this research, it has been shown that particle swarm optimization based schemes can be an efficient method for solving both static RWA in support of traditional connection optimal provisioning and dynamic RWA problem to support emerging services and applications in NGONs like ASON. The behaviour of proposed algorithms has been verified by extensive experiments.

Some potential future developments with PSO-based heuristic schemes are:

- **Lightpath reconfiguration in WDM networks**: NGONs are envisioned to have the ability to dynamic provision network resources to support on-demand channel provisioning for a finite amount of time. Efficient heuristic based dynamic RWA schemes like CPSO proposed in this thesis can enable the network control plane to achieve this. However, constant dynamic provisioning can lead to a sub-optimal network configuration as the logical network topology changes with the traffic patterns. This results from the persistence of long-lived connections on routes that subsequently could be better used for other purposes. To bring the network back to a near optimal state for maximizing network resource utilization, different topology reconfiguration algorithms have been proposed in literature [125, 126, 127 and 128] which re-route traffic demands to re-optimize the objective function. Work could include investigating a modified CPSO based heuristic scheme where only selected lightpaths in the current logical topology are reconfigured in an effort to optimize the objective function, instead of network-wide logical topology reconfiguration.

- **Energy conservation in optical networks**: Optical networks are one of the major communication network deployments around the globe and optical fibre deployment is constantly growing. According to an estimate, around 2 to 2.5 percent of the carbon footprint is caused by information and communication technologies as an industry [129]. PSO based intelligent network control plane can help reduce the energy consumption in NGONS, by minimizing the network resources required to provision connections and temporarily switching off certain transceivers in OCXs.

- **Scalability of interconnected WDM optical ring networks**: Optical ring networks featuring WDM allow mesh connectivity (and thus the best possible network performance) but their capacity is limited by the number of wavelengths available. Increasing the network capacity requires the interconnection of multiple rings, and this work explores how to do this efficiently in all-optical WDM networks. The approach taken would build upon the work on Routing and Wavelength Assignment (RWA) in WDM networks presented in this thesis, where particle swarm optimisation techniques are used to efficiently perform this NP-complete task. This work would apply these heuristic based techniques to interconnected WDM rings, and will determine the appropriate topology to use for their interconnection based on the constraints such as reducing the number of wavelength converters needed and the complexity of any optical cross-connects in the network.

# CHAPTER 10 CONCLUSIONS

The tremendous growth of data traffic over the years has incurred a great need to deploy high-speed transport networks. All-optical WDM networks are an attractive candidate to meet the non-diminishing bandwidth requirements of end users, emerging applications and services. One of the desirable features of Next Generation Optical Networks (NGONs) like Automatically Switched Optical Network (ASON) is their ability to dynamically provision network resources (lightpath establishment) for connection requests with low connection blocking probability and minimal connection set-up time.

In WDM networks, separate channels co-exist within a single optical fibre. End users communicate by setting up these optical channels called 'lightpaths' between them and the task of establishing a lightpath is known as Routing and Wavelength Assignment (RWA). RWA can be categorized into two types: static RWA and dynamic RWA. Successfully solving these NP-hard (Nondeterministic Polynomial time - hard) problems is critical to efficiently utilizing resources in optical networks. Traditional optimization techniques (like ILP) become very inefficient for solving NP-hard optimization problems. The computational complexity prevents them from producing optimized solutions in a dynamic environment due to the time constraints. Therefore different heuristic and stochastic algorithms are used to solve NP-hard optimization problems. In this thesis, nature inspired swarm intelligence based particle swarm optimization algorithms have been investigated to solve both static and dynamic RWA problems.

The main objective of static RWA is to provision a given set of connection requests while minimizing the network resources required i.e. number of wavelengths required. A novel PSO-lb algorithm is proposed in Chapter 5. Three strategies namely St (1), St (2) and St (3) are proposed to help guide the particles reach positions having good fitness values. Simulation results show that PSO-lb can achieve optimal/near-optimal solution in terms of number of wavelengths required to setup given set of connection requests. PSO-lb also performs significantly better as compared to other evolutionary algorithms like ACO [96] and GA [94], SP-FF, SP-MU algorithms in terms of maximum number of connections that can be provisioned within a given number of wavelengths. One disadvantage of PSO-lb algorithm is its ability of premature convergence especially for large problem search spaces. In Chapter 6, PSO-pb algorithm is proposed which significantly improves this problem. Simulation results presented in Chapter 5 and 6 show that PSO-lb and PSO-pb algorithms can efficiently solve static RWA problem to provision connections in traditional WDM networks.

In the case of dynamic RWA, the main objective is to minimize the blocking probability for the future connection requests. PSO algorithm is proposed in Chapter 7 to solve dynamic RWA problem. A novel fitness function is proposed that reduces the need to have dynamically adjustable 'α' factor which is used to control the influence of hop-length and number of free wavelengths on the fitness value of the particle. Blocking probability performance is crucial for efficient resource utilization. The proposed PSO algorithm performs better in terms of blocking probability performance compared to Genetic Algorithms (GAs) presented in [108] and [110]. It can also provision more connections for a given number of wavelengths compared to heuristic algorithms like ACO [96], SP-FF, SP-MU and so forth. Connection provisioning time is another vital performance measure to support services like bandwidth-on-demand supported by dynamic networks like ASON. PSO scheme performs significantly better in terms of route computation time relative to GA algorithms and can solve dynamic RWA problem within fraction of a second (Table 7.1).

One problem with the proposed PSO dynamic RWA solver is its slow convergence towards an optimal/near-optimal solution especially when the swarm size or maximum number of iterations allowed is limited. The CPSO algorithm proposed in Chapter 8 improves the overall performance of PSO as dynamic RWA solver by inducing randomness during position updating of the particles.

The superior blocking probability performance and short computation time make particle swarm optimization based algorithms (PSO and CPSO) a suitable candidate for connection provisioning in NGONs like ASON. Results show that the approach typically outperforms other evolutionary schemes by a considerable margin both in terms of "goodness" of solution and reduced computational complexity.

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# Appendix A: Hybrid Network Resource Provisioning System for NGONs

A hybrid system has been implemented in Opnet 14.5 [118] to study resource provisioning in circuit switched NGON like ASON, GMPLS based optical networks. Some of the salient features of the architecture are:

- The architecture can be used to investigate PSO based static RWA provisioning algorithms like PSO-lb (Chapter 5) and PSO-pb (Chapter 6)
- It can also be used to investigate various traditional dynamic RWA provisioning algorithms like SP-FF, SP-MU etc as well as swarm intelligence heuristic schemes like PSO (Chapter 7), Genetic algorithms proposed in [108], [110] and CPSO (Chapter 8).
- The hybrid architecture can be modified to simulate fully centralized resource provisioning system where a centralized node does computation to solve RWA problem. Here, centralised node has global knowledge and makes the resource allocation decisions. A fully distributed network resource provisioning system can also be simulated where each node does RWA computation locally in a distributed fashion. The later scheme faces a disadvantage of resource conflict where more than one connection competes for the same network resource simultaneously and therefore increase blocking probability.
- Architecture also provides facility to analyse fully centralized connection request generator where only the centralized node generates connection requests. Or it can be fully distributed traffic generation system, where each node in the network can generate connection requests.

## A.1. Information Collection (Centralized vs. Distributed approach)

In a dynamic environment, connections are provisioned and torn-down dynamically. Therefore, the network state doesn't remain constant and changes over the time. In order to produce better deployment results for upcoming connection requests, it is essential for the network management and control system to collect the state information as quickly and precisely as possible. The information collection of a network control system can be carried out in a centralized mode or a distributed mode.

### A.1.1. Centralized Mode

In the centralized mode, as employed in Simple Network Management Protocol (SNMP), the detailed network state information is collected and maintained by a Network Management Station (NMS) as shown in figure A.1. This is done through communication between the NMS and each managed node in the network. Using centralised node avoids temporal conflicts as one node has global knowledge and only it makes the resource allocation decisions. A centralized network information collection mechanism is easy to implement, either through NMS-controlled polling or by setting trigger thresholds that cause the managed entities to report exceptional events. If the information collection mechanism is centralized, this approach is often coupled with centralized control of the network. For example, in the context of optical-connection management, when there is a connection request, it would be sent to the centralized manager. This would then calculate the deployment route based on the centrally held network information; it would then send appropriate connection commands to the network nodes to set up the connection.

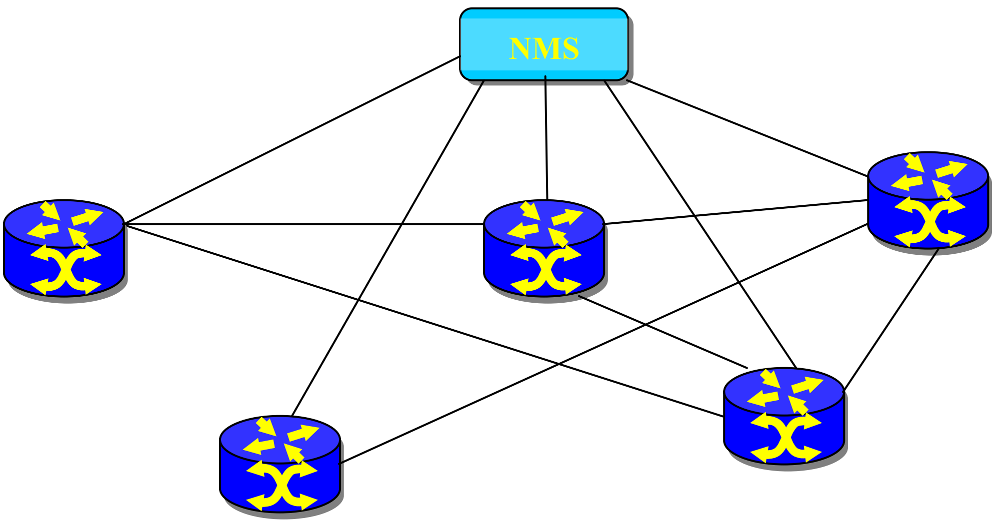


**Figure A.1: Centralized Network connection Management System**

However, such an approach has some disadvantages. Setting up and maintaining a NMS is expensive as the communication between centralized node and the rest needs to be extremely reliable as they makeup the control plane (brain) of the network. Additional strategies are required to protect the centralized server and its communication with each node in the network. Such a mode of network operation also requires the centralized node to have high processing capability if the connection requests are quite frequent.

### A.1.2. Distributed Mode

In contrast, distributed control is more robust than centralised control. The distributed solution eliminates the sole responsibility of the centralised controller to collect network information and to manage connections. In distributed mode, every node maintains a network state database and traffic information. Each node also contributes to the connection management. The local database is maintained and synchronized using a link state routing protocol, such as extended Open Shortest Path First (OSPF) and the Intermediate System-to-Intermediate System protocol (IS-IS). Using these link state routing protocols, information on each link is *flooded* to every node in the network. Therefore, each node will have the same network state information. Path calculation is done using the information contained in the local database. Since collection of network state information and connection management is done by each node in distributed mode, this eliminates single point of failure and the need to have a centralized node with high processing capability. Since the path calculation for each connection request is done at the ingress node, it is faster than the centralized mode of operation since it does not need time to communicate with the central point.

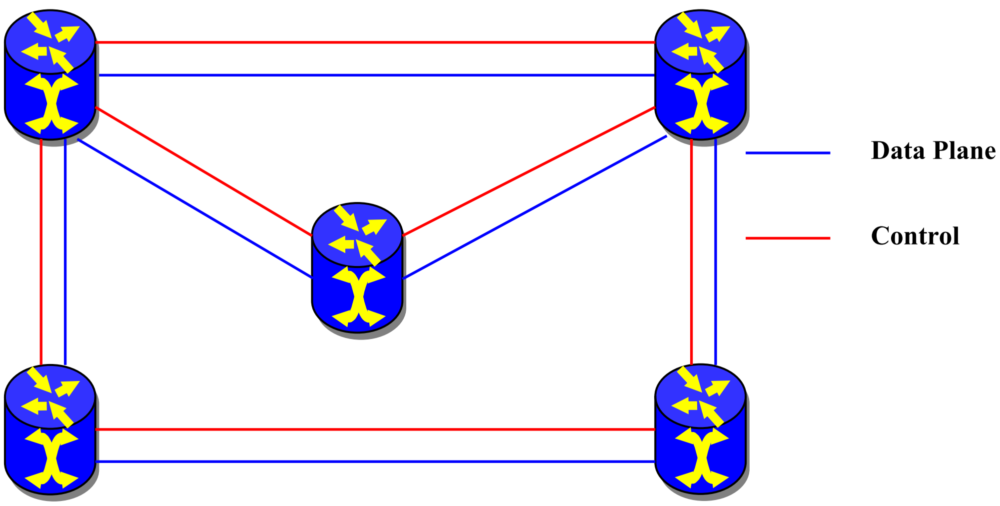


**Figure A.2: Distributed Network connection Management System**

However, a disadvantage of distributed network control and connection management system is the network state database consistency. To ensure accurate and consistent connection provisioning decisions made by each ingress node, local network state databases of all the nodes needs to be synchronized. After each connection provisioning by any ingress node, any change in the network state database needs to be updated in all local databases as quickly as possible. To do this, more information flooding is required which means more time for the local databases to converge. The latency in information convergence can lead to inconsistent local information among the nodes and ultimately will lead to inappropriate connection placements. One solution is to flood only aggregated information about each link, which enables the database at each node to be updated more quickly by sacrificing some detailed link information.

## A.2. Path Calculation (Sophisticated Offline vs. Online)

Route computation (path calculation) is an important network control plane function. Two main strategies for path calculation can be used for this, which are:

- Offline path calculation
- Online path calculation

In offline mode, sophisticated network resource optimization schemes like ILP can be used to search globally optimized paths. ILP is usually used for solving static routing and wavelength assignment problem in static network control systems. However, such global optimization schemes are time consuming and require huge computational power. Therefore, such techniques are unsuitable for dynamic environment requiring real-time solutions. In addition, in dynamic network, connection requests arrive individually without knowledge of concurrent requests or future demands; this also affects performance of such schemes.

In online mode, path from source to destination node is computed individually without taking into account connections already deployed. Typical and widely used examples of such algorithms are Shortest Path First (SPF), Constraint-based SPF (CSPF), and Open Shortest Path First (OSPF) etc. These IP based routing protocols make path calculation decisions individually, for each connection, without exact information concerning all the traffic. The goal of these protocols is to find suitable deployment for newly arriving connection requests based on the current network state. However, lack of awareness of concurrent, spatially-separate setup requests and the limited detail of the link state database can lead to sub-optimal deployment.

## A.3. Traffic Assumptions (Long lived vs. Short lived Connections)

In a dynamic environment, categorization of lightpath requests as long lived and short lived connection can help us to improve not only resource provisioning, but also resource management.

If all or some of the connection requests are known in advance (static RWA), we can use some global heuristic scheme to provision resources for the given set of lightpath requests. Such collective resource provision will lead to better resource provisioning by saving network resources, as compared to dynamic resource provisioning (dynamic RWA) as shown in the example below. Suppose three lightpath (1, 5), (2, 3), (1, 3) arrives at time $T_1$, $T_2$ and $T_3$ sequentially. Dynamic RWA is employed with an objective function of minimizing the number of wavelengths required. Let's say first-fit wavelength assignment algorithm is used for wavelength-assignment sub-problem. At time $T_1$, a connection request arrives to setup a lightpath between node '1' and node '5'. The chosen route is the shortest path i.e. $1 \rightarrow 3 \rightarrow 5$, between source-destination nodes. Using first-fit scheme, wavelength $\lambda_1$ is used as shown in figure A.3a.

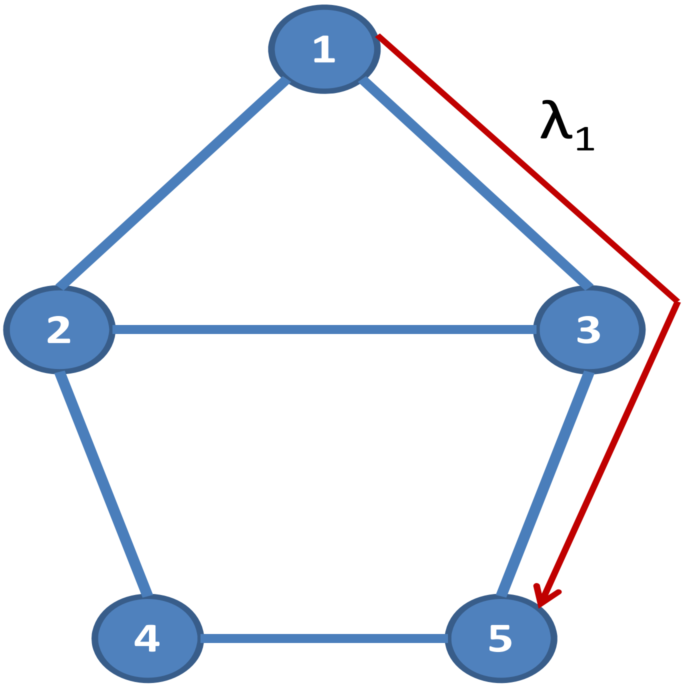


**Figure A.3a: Lightpath request (1, 5) arriving at time T1. Wavelength being used: λ1**

At time $T_2$, second connection request arrives to setup a lightpath between node '2' and node '3'. The chosen route is 2→ 3 and wavelength $\lambda_1$ is chosen as shown in figure A.3b.

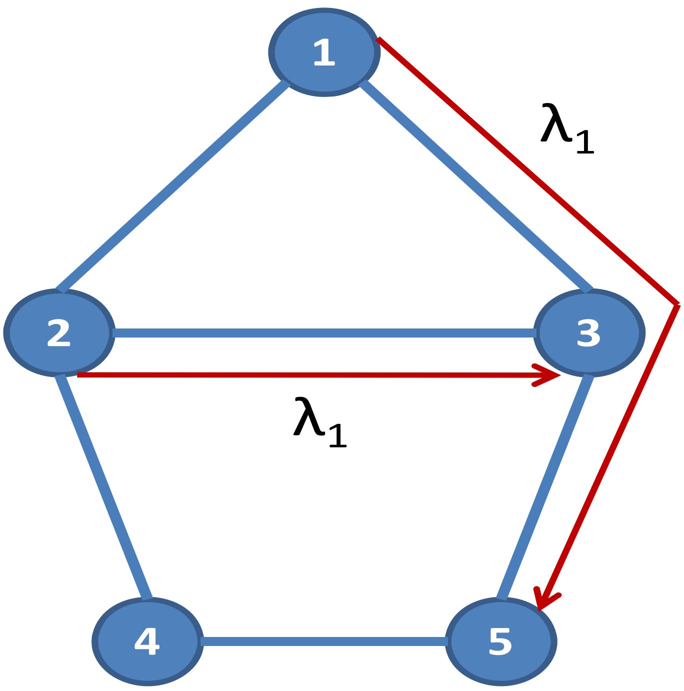


**Figure A.3b: Lightpath request (2, 3) arriving at time T2. Wavelength being used: λ1**

At time $T_3$, third connection request arrives to setup a lightpath between node '1' and node '3'. In this case, whatever route we choose for this connection request now, we can't use wavelength $\lambda_1$ because of "wavelength clash constraint". Thus we need an additional wavelength $\lambda_2$. So to setup three lightpath requests, we have utilized two wavelengths. On the other hand, if we have a traffic prediction scheme that can accurately predict the future traffic (static RWA), we can use some global heuristic scheme or ILP with an objective function of minimizing the number of wavelengths required. This can lead to lightpath deployment as shown in figure A.3c where only one wavelength is used to establish three lightpaths (1, 5), (2, 3) and (1, 3).

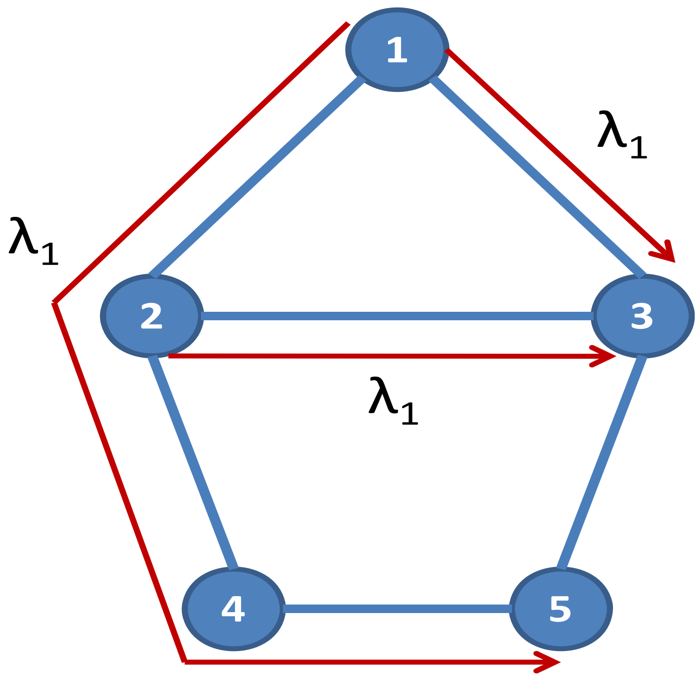


**Figure A.3c: Lightpath requests (1, 5), (2, 3) and (1, 3) deployed using only one wavelength λ1.**

However the computation time required doing static RWA makes it unusable in a dynamic environment. Computing appropriate routes and wavelengths (RWA) for a set of lightpaths, collectively, is more computationally expensive as compared to RWA computation done for each lightpath individually. Also it would be useless to do static RWA for a lightpath (among others) which is going to stay for a very short time (few seconds). Therefore, characterization of lightpath can help us to reduce the problem space for static RWA by using dynamic RWA schemes for short lived connections and using static RWA only for long-lived connections.

For optimal network resource management, re-deployment of lightpaths can be used to bring the network configuration back to optimality. Re-deployments being an expensive operation of the management plane need to be minimized. It would be useless to re-deploy a lightpath which is going to stay for few seconds. This characterization of lightpaths can help to reduce the number of lightpath re-deployments required, by redeploying only long-lived lightpaths.

There are number of ways in which network control plane can categorize lightpaths setup over the network as short-lived or long lived, which are:

- Asking clients (users, applications, services etc) to explicitly mention the approximate time for which they need connection over the network.
- Estimating approximate time for which light path will stay in the network based on historical usage patterns of clients, the kind of service/application which has requested the connection, basis on subscription type etc.
- For lightpath re-deployments, estimation timers can also be used. When a lightpath is provisioned, start a timer. If lightpath does not tear down, and continue to stay after time‘t’, mark that lightpath as long-lived connection. Time‘t’ will be defined by the control plane.

## A.4. Functional Model of Hybrid System

OPNET [118] is used to simulate and evaluate the effectiveness of a hybrid architecture for intelligent resource provisioning system. This section explains the models implemented within simulation and description of functional model of the system as shown in the figure A.4.

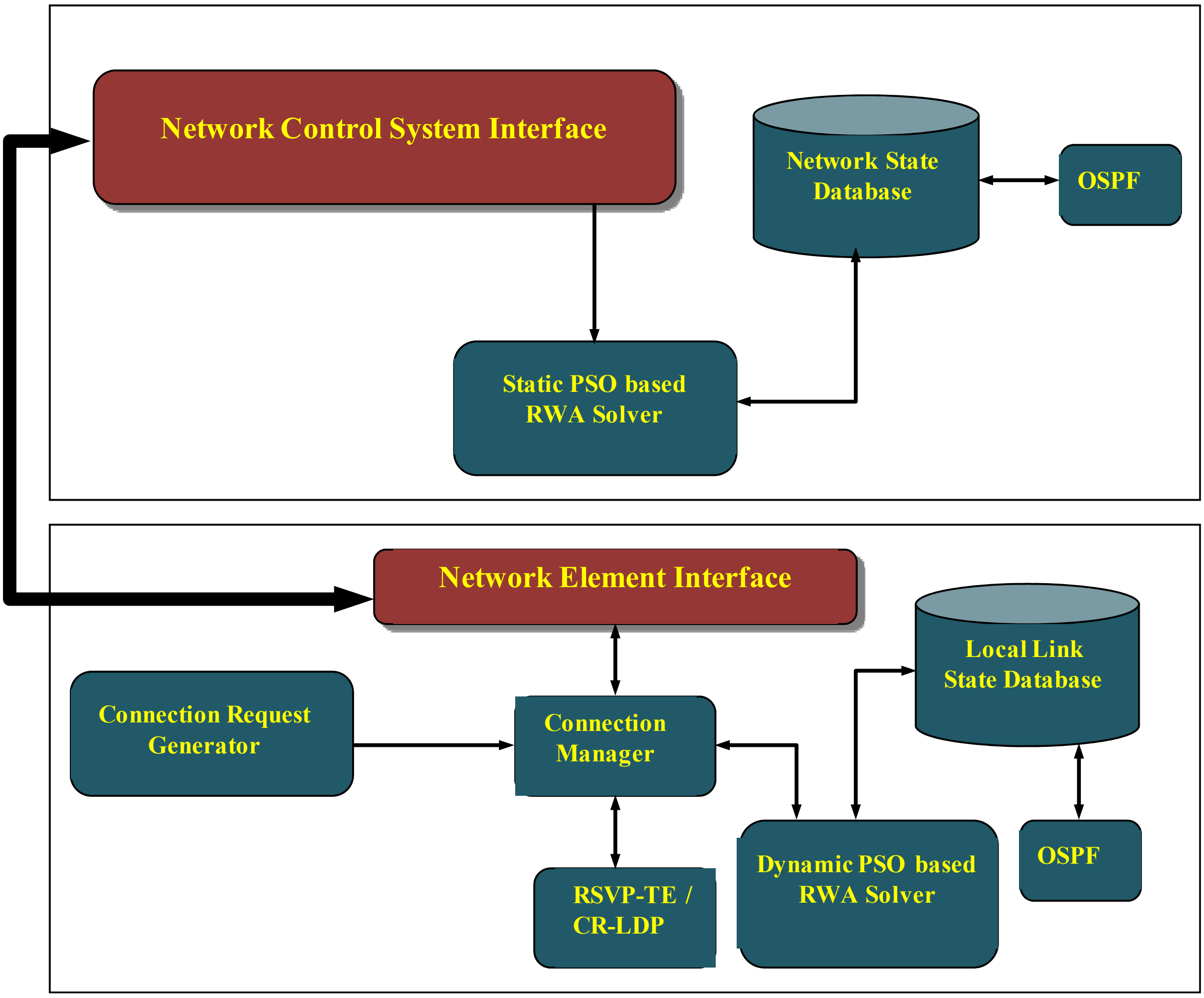


**Figure A.4: Proposed Hybrid Architecture for intelligent Resource Provisioning System**

The intelligent resource management system consists of two major physical entities. One is Network Control System (NCS) and other is Network Element (NE). NE is implemented inside each node of the optical network. The NCS is a specialized, centralized node. In this hybrid architecture, a part of the functionality of resource management system is distributed among all nodes of the network as NE. However, part of the functionality resides in the NCS which will do centralized RWA computation to find optimal configuration when a set of connection request are given.

The NCS is modelled as an OPNET *node model*. Each optical network will have just one NCS node. The main components of NCS include NCS-interface which will provide an interface for different functional blocks of NCS and NE-interface to communicate with each other, PSO based static RWA solver to compute an optimal/near-optimal solution, when a set of connection requests are given and a detailed Network State Database (DB) to maintain information about each network element in the network and the links between them. The PSO-based static RWA solver will use centralized network state information to solve static RWA.

The NE is also modelled as an OPNET *node model*. Each NE consists of a NE-interface which will provide an interface for different functional blocks of NE and NCS-interface to communicate with each other, a connection manager to set up and tear down a connection, a connection request generator, an online dynamic PSO function block to compute routes dynamically in very short time (milliseconds), GMPLS based RSVP-TE / CR-LDP signalling engine and the OSPF link state database (LSDB). Notice here that the service generator function entity is implemented within the network element. So each node in the network can be a potential source or destination node of the lightpath connection request.

Each node can initiate a call using a connection request generator and become the ingress node of a connection. For each connection request, the connection manager in NE will request dynamic PSO function block to compute appropriate route and a wavelength for the lightpath request dynamically. Simulation model of NE along with the messages between different node elements is shown in the figure A.5.

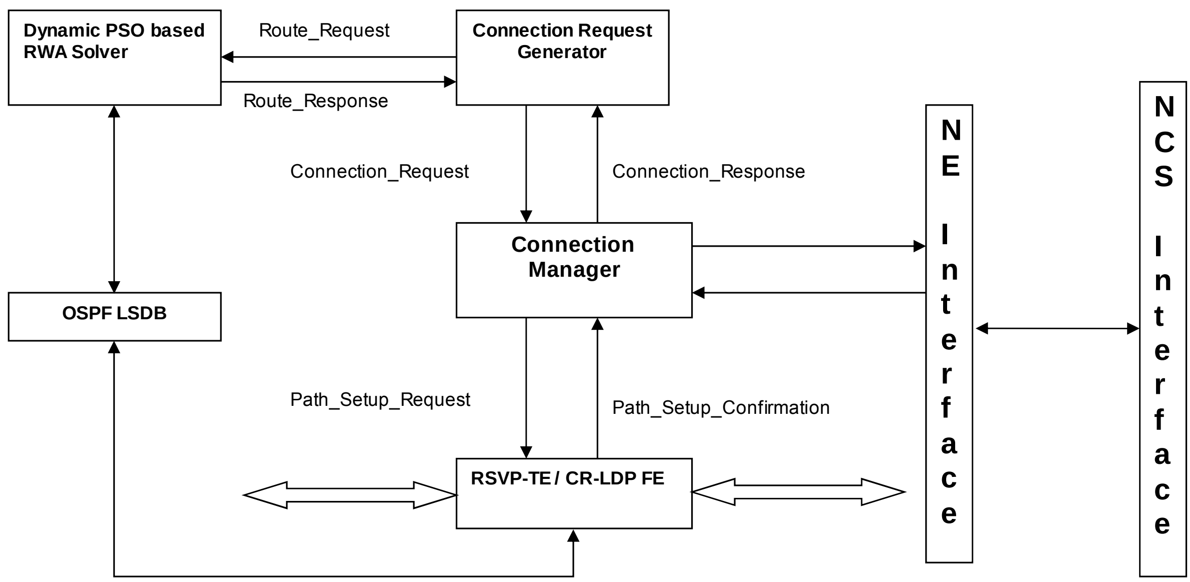


**Figure A.5: Simulation Model of Network Element (NE)**

### A.4.1. Connection Request Generator

The connection request generator automatically produces requests to set up connections. The traffic generated can be differentiated into two main groups, short-lived connections and long-lived connections. Short-lived connections will stay in the network for a brief time span. Long-lived connections are assumed to stay in the network for a significant amount of time. The time limit to differentiate between short-lived and long-lived connection requests depends on the traffic characteristic which needs to be investigated and is beyond the scope this thesis.

Next Generation Optical Networks like ASON represents a promising technology in offering flexibility and convenience of bandwidth allocation by offering services like Bandwidth-on-Demand (BoD) services. This evolution towards intelligent optical networking is driven by the growing importance of traffic that requires high bandwidth on-demand switched connections for its efficient transportation.

An important activity in planning such novel transport networks is the selection of suitable *traffic model(s)* to represent dynamic component of the traffic and to evaluate the effectives of various resource management mechanisms under a number of use-case scenarios. As ASON systems do not exist there are no "real-world" sources of data available from which to characterise the models. This is particularly true of the short-lived traffic as services of this type are unlikely to be popular under the existing leased-line regime.

In the past, some classical teletraffic models like *Poisson,* the *Engset* and the *Fredericks* models have been used by researchers for circuit-switched networks, to describe the user connection request pattern. Like traditional circuit-switched networks, ASON allow the end users to dynamically establish connections to other end-nodes in the network. The connection establishment process, connection holding and release process in the case of ASON is similar to traditional circuit-switched networks. But unlike traditional circuit switched networks, three different kinds of connections can exist simultaneously over the ASON, which are (a) Permanent Connections (b) Soft Permanent Connections (c) Switched Connections. Permanent connection The soft permanent service is requested by the management plane, which uses network generated signalling and routing protocols (RSVP-TE and OSPF-TE) via the Network-Network Interface (NNI) to establish the connections, while the switched service can be requested directly by the customers via the User Network Interface (UNI) signalling and then the connections are set-up using NNI. Investigation of different traffic models for simulating traffic in NGONs is beyond the scope of this thesis and therefore, traditional mathematical models like *Poisson*, *Engset*, *Fredricks* etc, have been used based on traditional negative-exponential call holding times. Although not realistic, such models lend themselves to analysis, which is useful for verification; they are also frequently used by other researchers and therefore provide a useful point of comparison.

### A.4.2. Connection Manager

This module takes charge and monitors the path setup of every connection request. For each connection request, it requests Dynamic PSO RWA solver to compute appropriate route and wavelength for the connection request. Connection manager than passes the route and wavelength information to GMPLS based RSVP-TE / CR-LDP signalling engine to setup connection request in the network. For each connection request, the connection manager initiates only one connection establishment attempt. If the connection attempt fails, the connection is then blocked. Investigating the effect of number of re-attempts on the blocking probability performance and over all network resource management is beyond the scope of this thesis.

### A.4.3. Static PSO based RWA Solver

This module uses a novel PSO-bases approach (PSO-pb) to solve routing and wavelength assignment problem, when a set of connection requests are given. This module is included to support the legacy long-lived connection request which stays in the network for years and therefore must be provisioned optimally. Detailed explanation PSO based static RWA solver can be found in Chapter 6.

### A.4.4. Online (dynamic) PSO based RWA Solver

This module uses a novel PSO-based approach (PSO/CPSO) to solve dynamic routing and wavelength assignment problem for a specific connection request dynamically. Detailed explanation of PSO-based dynamic RWA solvers can be found in Chapter 7 and 8 of this thesis.

### A.4.5. GMPLS based RSVP-TE / CR-LDP Functional Entity (FE)

This module acts as the signalling process which realises most of the major function of RSVP-TE / CR-LDP with GMPLS signalling extensions [130, 131 and 132]. The local LSDB records detailed port and link information.

### A.4.6. OSPF LSDB

This module maintains a database that records the aggregated link state of the simulation network. The online dynamic RWA solver will use this aggregated link state information provided by LSDB to compute routes and to choose appropriate wavelength for the connection request.

### A.4.7. Communication Procedures and Messages

Figure A.6 shows the connection establishment procedure when a batch of connection requests is given to PSO-bases static RWA solver block in NCS. After RWA computation, the NCS requests NE module of concerning nodes to provision resources appropriately for establishment of lightpaths. Once connection has been established, a Connection Report message is also sent to the Network Control System to refresh the centralized link state database.

Figure A.7 shows the RWA computation procedure when a dynamic connection request is generated by traffic generator. Connection Manager sends a route computation request to the dynamic RWA solver. The online proposed RWA solver here computes the route for the current connection request by retrieving information from the local link state database. The information is then used to compute route of the connection. If the Connection Manager receives route from dynamic RWA solver, connection is established. If no route can be computed, the connection is blocked.

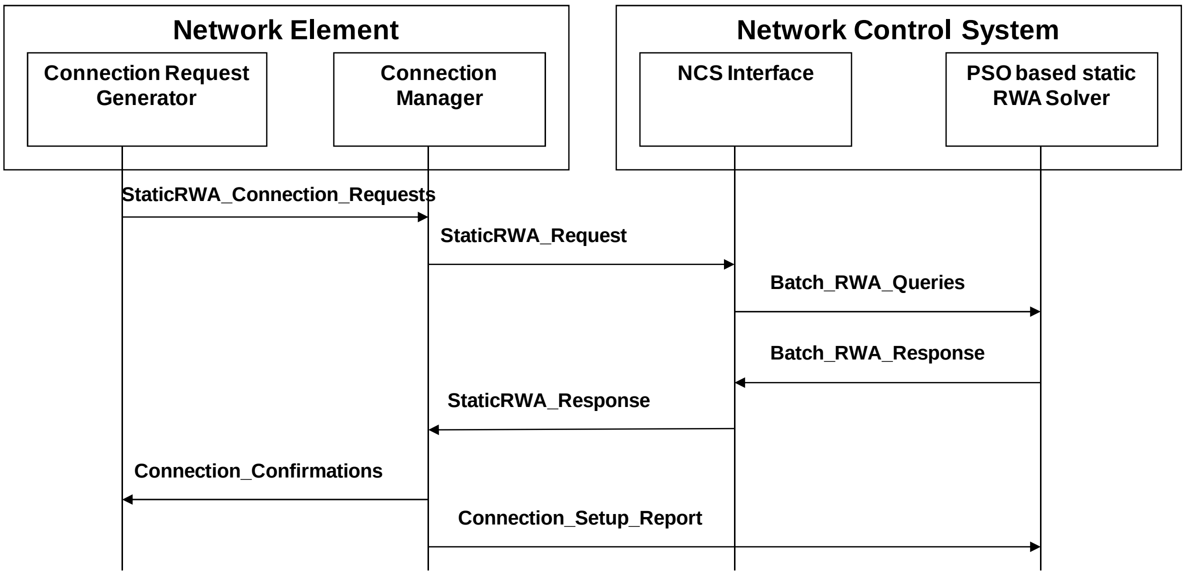


**Figure A.6: PSO-based StaticRWA computation to support Legacy or Long Lived Optical Connections**

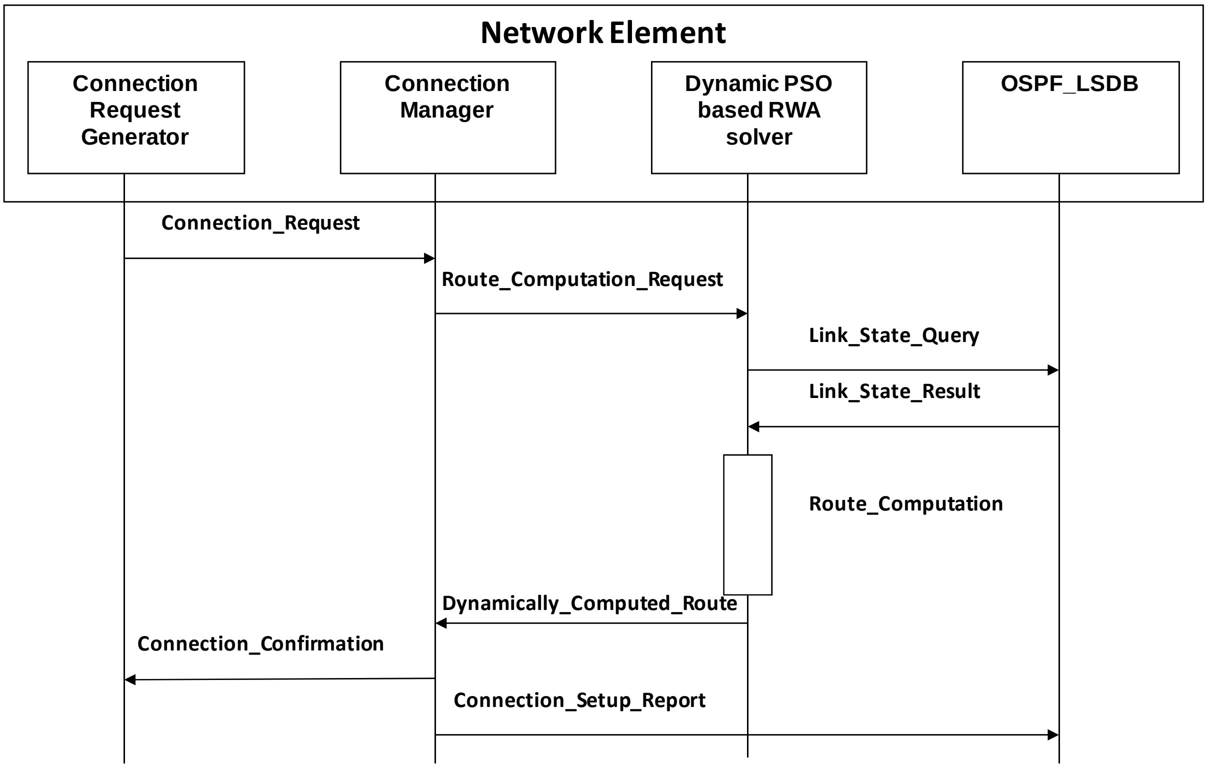


**Figure A.7: RWA Computation Procedure to support dynamic services like Bandwidth-on-Demand**

When Connection Manager receives a route for the connection request from PSO based dynamic RWA solver, procedure to setup connection using GMPLS based signalling is shown in the figure A.8.

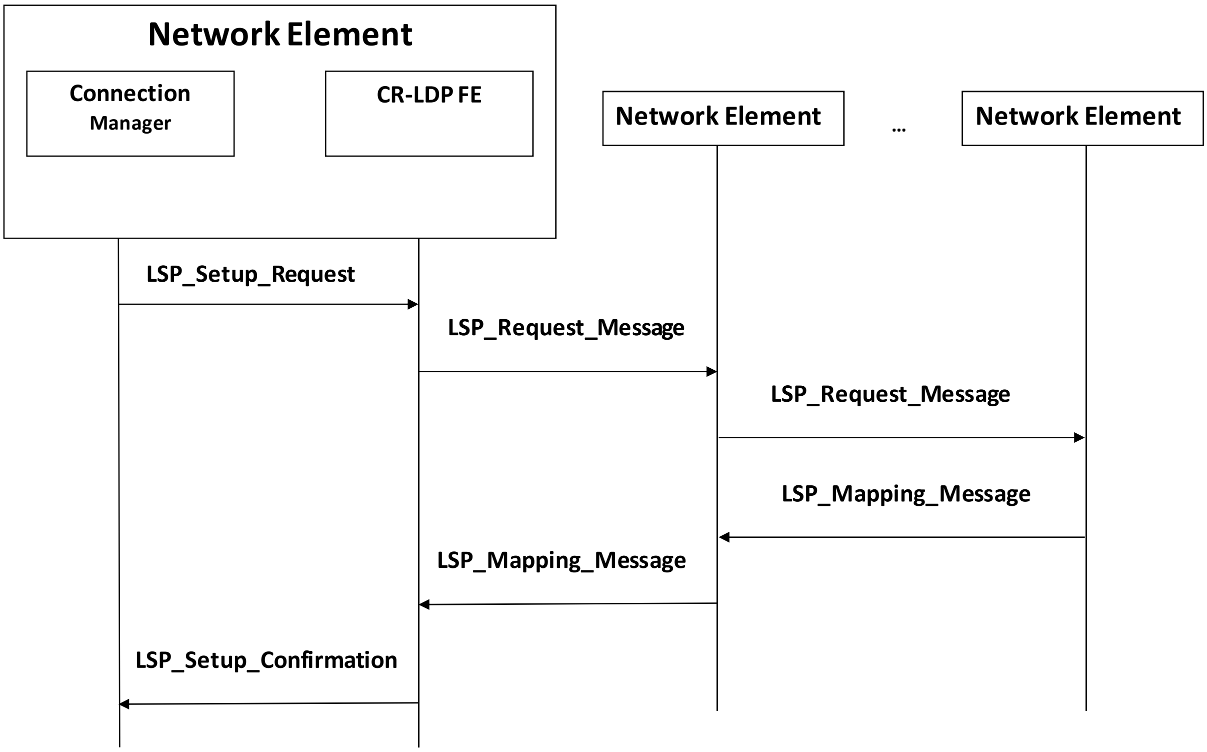


**Figure A.8: Procedure to Setup Connection using GMPLS Signalling**

# Appendix B – Validation Data for PSO-lb based Static RWA

14 nodes, 21 edges NSFNET shown in figure 4.2 is assumed. Total number of connection requests equals N*(N-1) where 'N' is the total number of nodes in the network. PSO-lb algorithm is used to solve static RWA problem.

Number of particles = 14, Maximum number of iterations allowed = 3500, NS = 3, KSP = 2

Total Number of wavelengths required: 13, APL = 2.3626

Iteration number when last improvement is made = 1368.3

Selected routes for the given set of connection request are as follows.

| **Connection#** | **Source node→Destination node** | **Chosen Route** |
|---|---|---|
| (1) | 1→2 | (1, 2) |
| (2) | 1→3 | (1, 3) |
| (3) | 1→4 | (1, 4) |
| (4) | 1→5 | (1, 4, 5) |
| (5) | 1→6 | (1, 3, 6) |
| (6) | 1→7 | (1, 2, 8, 7) |
| (7) | 1→8 | (1, 3, 2, 8) |
| (8) | 1→9 | (1, 3, 6, 9) |
| (9) | 1→10 | (1, 3, 6, 10) |
| (10) | 1→11 | (1, 4, 12, 13, 11) |
| (11) | 1→12 | (1, 4, 12) |
| (12) | 1→13 | (1, 3, 6, 10, 13) |
| (13) | 1→14 | (1, 4, 12, 14) |
| (14) | 2→1 | (2, 1) |
| (15) | 2→3 | (2, 3) |
| (16) | 2→4 | (2, 3, 1, 4) |
| (17) | 2→5 | (2, 8, 7, 5) |
| (18) | 2→6 | (2, 1, 4, 5, 6) |
| (19) | 2→7 | (2, 8, 7) |
| (20) | 2→8 | (2, 8) |
| (21) | 2→9 | (2, 1, 3, 6, 9) |
| (22) | 2→10 | (2, 3, 6, 10) |
| (23) | 2→11 | (2, 8, 11) |
| (24) | 2→12 | (2, 1, 4, 12) |
| (25) | 2→13 | (2, 3, 6, 10, 13) |
| (26) | 2→14 | (2, 8, 11, 14) |
| (27) | 3→1 | (3, 1) |
| (28) | 3→2 | (3, 1, 2) |
| (29) | 3→4 | (3, 2, 1, 4) |
| (30) | 3→5 | (3, 2, 1, 4, 5) |
| (31) | 3→6 | (3, 6) |
| (32) | 3→7 | (3, 2, 8, 7) |
| (33) | 3→8 | (3, 2, 8) |
| (34) | 3→9 | (3, 2, 8, 11, 9) |
| (35) | 3→10 | (3, 6, 10) |

| Connection# | Source node→Destination node | Chosen Route |
|---|---|---|
| (36) | 3→11 | (3, 6, 9, 11) |
| (37) | 3→12 | (3, 1, 4, 12) |
| (38) | 3→13 | (3, 6, 10, 13) |
| (39) | 3→14 | (3, 6, 10, 14) |
| (40) | 4→1 | (4, 1) |
| (41) | 4→2 | (4, 1, 2) |
| (42) | 4→3 | (4, 1, 3) |
| (43) | 4→5 | (4, 5) |
| (44) | 4→6 | (4, 5, 6) |
| (45) | 4→7 | (4, 5, 7) |
| (46) | 4→8 | (4, 1, 2, 8) |
| (47) | 4→9 | (4, 12, 14, 11, 9) |
| (48) | 4→10 | (4, 5, 6, 10) |
| (49) | 4→11 | (4, 12, 13, 11) |
| (50) | 4→12 | (4, 12) |
| (51) | 4→13 | (4, 12, 13) |
| (52) | 4→14 | (4, 12, 14) |
| (53) | 5→1 | (5, 4, 1) |
| (54) | 5→2 | (5, 4, 1, 2) |
| (55) | 5→3 | (5, 7, 8, 2, 3) |
| (56) | 5→4 | (5, 4) |
| (57) | 5→6 | (5, 6) |
| (58) | 5→7 | (5, 7) |
| (59) | 5→8 | (5, 7, 8) |
| (60) | 5→9 | (5, 6, 9) |
| (61) | 5→10 | (5, 6, 10) |
| (62) | 5→11 | (5, 6, 9, 11) |
| (63) | 5→12 | (5, 4, 12) |
| (64) | 5→13 | (5, 4, 12, 13) |
| (65) | 5→14 | (5, 6, 10, 14) |
| (66) | 6→1 | (6, 3, 1) |
| (67) | 6→2 | (6, 3, 2) |
| (68) | 6→3 | (6, 3) |
| (69) | 6→4 | (6, 5, 4) |
| (70) | 6→5 | (6, 5) |
| (71) | 6→7 | (6, 5, 7) |
| (72) | 6→8 | (6, 5, 7, 8) |
| (73) | 6→9 | (6, 9) |
| (74) | 6→10 | (6, 10) |
| (75) | 6→11 | (6, 9, 11) |
| (76) | 6→12 | (6, 5, 4, 12) |
| (77) | 6→13 | (6, 9, 11, 13) |
| (78) | 6→14 | (6, 9, 11, 14) |
| (79) | 7→1 | (7, 8, 2, 1) |
| (80) | 7→2 | (7, 8, 2) |
| (81) | 7→3 | (7, 5, 6, 3) |
| (82) | 7→4 | (7, 5, 4) |
| (83) | 7→5 | (7, 5) |
| (84) | 7→6 | (7, 5, 6) |
| (85) | 7→8 | (7, 8) |
| (86) | 7→9 | (7, 8, 11, 9) |
| (87) | 7→10 | (7, 5, 6, 10) |
| (88) | 7→11 | (7, 8, 11) |
| (89) | 7→12 | (7, 8, 11, 13, 12) |
| (90) | 7→13 | (7, 8, 11, 13) |

| Connection# | Source node→Destination node | Chosen Route |
|---|---|---|
| (91) | 7→14 | (7, 8, 11, 14) |
| (92) | 8→1 | (8, 2, 3, 1) |
| (93) | 8→2 | (8, 2) |
| (94) | 8→3 | (8, 2, 3) |
| (95) | 8→4 | (8, 7, 5, 4) |
| (96) | 8→5 | (8, 7, 5) |
| (97) | 8→6 | (8, 7, 5, 6) |
| (98) | 8→7 | (8, 7) |
| (99) | 8→9 | (8, 7, 5, 6, 9) |
| (100) | 8→10 | (8, 11, 14, 10) |
| (101) | 8→11 | (8, 11) |
| (102) | 8→12 | (8, 11, 13, 12) |
| (103) | 8→13 | (8, 11, 13) |
| (104) | 8→14 | (8, 11, 13, 10, 14) |
| (105) | 9→1 | (9, 6, 3, 1) |
| (106) | 9→2 | (9, 6, 3, 1, 2) |
| (107) | 9→3 | (9, 11, 8, 2, 3) |
| (108) | 9→4 | (9, 6, 5, 4) |
| (109) | 9→5 | (9, 6, 5) |
| (110) | 9→6 | (9, 6) |
| (111) | 9→7 | (9, 6, 5, 7) |
| (112) | 9→8 | (9, 6, 5, 7, 8) |
| (113) | 9→10 | (9, 11, 14, 10) |
| (114) | 9→11 | (9, 11) |
| (115) | 9→12 | (9, 11, 13, 12) |
| (116) | 9→13 | (9, 11, 13) |
| (117) | 9→14 | (9, 11, 14) |
| (118) | 10→1 | (10, 6, 5, 4, 1) |
| (119) | 10→2 | (10, 6, 3, 2) |
| (120) | 10→3 | (10, 6, 3) |
| (121) | 10→4 | (10, 6, 3, 1, 4) |
| (122) | 10→5 | (10, 13, 12, 4, 5) |
| (123) | 10→6 | (10, 6) |
| (124) | 10→7 | (10, 14, 11, 8, 7) |
| (125) | 10→8 | (10, 13, 11, 8) |
| (126) | 10→9 | (10, 6, 9) |
| (127) | 10→11 | (10, 14, 11) |
| (128) | 10→12 | (10, 14, 12) |
| (129) | 10→13 | (10, 13) |
| (130) | 10→14 | (10, 14) |
| (131) | 11→1 | (11, 8, 2, 1) |
| (132) | 11→2 | (11, 8, 2) |
| (133) | 11→3 | (11, 9, 6, 3) |
| (134) | 11→4 | (11, 13, 12, 4) |
| (135) | 11→5 | (11, 8, 7, 5) |
| (136) | 11→6 | (11, 9, 6) |
| (137) | 11→7 | (11, 8, 7) |
| (138) | 11→8 | (11, 8) |
| (139) | 11→9 | (11, 9) |
| (140) | 11→10 | (11, 14, 10) |
| (141) | 11→12 | (11, 13, 12) |
| (142) | 11→13 | (11, 13) |
| (143) | 11→14 | (11, 14) |
| (144) | 12→1 | (12, 4, 1) |
| (145) | 12→2 | (12, 4, 1, 2) |

| Connection# | Source node→Destination node | Chosen Route |
|---|---|---|
| (146) | 12→3 | (12, 4, 1, 3) |
| (147) | 12→4 | (12, 4) |
| (148) | 12→5 | (12, 4, 5) |
| (149) | 12→6 | (12, 13, 10, 6) |
| (150) | 12→7 | (12, 4, 5, 7) |
| (151) | 12→8 | (12, 14, 11, 8) |
| (152) | 12→9 | (12, 13, 11, 9) |
| (153) | 12→10 | (12, 13, 10) |
| (154) | 12→11 | (12, 13, 11) |
| (155) | 12→13 | (12, 13) |
| (156) | 12→14 | (12, 14) |
| (157) | 13→1 | (13, 12, 4, 1) |
| (158) | 13→2 | (13, 10, 6, 3, 2) |
| (159) | 13→3 | (13, 12, 4, 1, 3) |
| (160) | 13→4 | (13, 12, 4) |
| (161) | 13→5 | (13, 11, 9, 6, 5) |
| (162) | 13→6 | (13, 11, 9, 6) |
| (163) | 13→7 | (13, 10, 6, 5, 7) |
| (164) | 13→8 | (13, 11, 8) |
| (165) | 13→9 | (13, 10, 14, 11, 9) |
| (166) | 13→10 | (13, 10) |
| (167) | 13→11 | (13, 11) |
| (168) | 13→12 | (13, 12) |
| (169) | 13→14 | (13, 10, 14) |
| (170) | 14→1 | (14, 10, 6, 3, 1) |
| (171) | 14→2 | (14, 11, 8, 2) |
| (172) | 14→3 | (14, 11, 8, 2, 3) |
| (173) | 14→4 | (14, 10, 13, 12, 4) |
| (174) | 14→5 | (14, 10, 6, 5) |
| (175) | 14→6 | (14, 10, 6) |
| (176) | 14→7 | (14, 12, 4, 5, 7) |
| (177) | 14→8 | (14, 11, 8) |
| (178) | 14→9 | (14, 11, 9) |
| (179) | 14→10 | (14, 10) |
| (180) | 14→11 | (14, 11) |
| (181) | 14→12 | (14, 12) |
| (182) | 14→13 | (14, 10, 13) |

**The wavelengths assigned to the selected routes are:**

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Route-ids of the routes assigned WAVELENTH # 1
40   47   134   220   395   423   471   451   533   602   510   53   169
661
Route-ids of the routes assigned WAVELENTH # 2
71   99   188   354   630   21   310   429   581   525   613   105   229
329   517   713   721
Route-ids of the routes assigned WAVELENTH # 3
83   414   426   447   484   486   67   193   213   241   558   709   621
Route-ids of the routes assigned WAVELENTH # 4
119   495   636   644   678   85   101   245   253   233   1   369   513
565
Route-ids of the routes assigned WAVELENTH # 5
650   686   691   26   49   142   189   342   378   417   161   569   617
665
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Route-ids of the routes assigned WAVELENTH # 6
659 703 29 62 125 301 314 321 398 457 497 157 293
437 489
Route-ids of the routes assigned WAVELENTH # 7
33 93 181 286 306 366 386 473 605 506 589 725 221
401 549 669
Route-ids of the routes assigned WAVELENTH # 8
114 149 357 441 537 577 594 173 205 261 297 373 5
77 553 717
Route-ids of the routes assigned WAVELENTH # 9
145 153 361 521 530 597 693 73 165 237 325 461 609
57
Route-ids of the routes assigned WAVELENTH # 10
258 405 646 681 13 17 110 129 201 209 281 381 465
477 289 337 585
Route-ids of the routes assigned WAVELENTH # 11
345 625 41 89 177 265 273 317 501 541 545 673 121
453
Route-ids of the routes assigned WAVELENTH # 12
137 249 333 349 433 561 573 653 697 9 269 389
Route-ids of the routes assigned WAVELENTH # 13
409 637 705 197 225 277