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Identifying Efficient Method for Resource Wavelength Assignment-A Survey

[1]J.P. Jaslin Sheeja and [2]K. Sheela Sobana Rani
[1]Anna University, Chennai,
Tamil Nadu, India.
jaslinsheeja@gmail.com
[2]Department of Electronics and Communication,
SRIT, Coimbatore,
Tamil Nadu, India.

Abstract

Wavelength division multiplexing (WDM) is a promising technology used in today's telecommunication systems to meet high bandwidth requirements. The optical network uses optical fibers as a transmission medium and the capacity of a single fiber can vary between 40Tb/s to 50Tb/s. Here, each bandwidth can be divided into smaller bands and it can be used concurrently to transfer the data. This is done with the help of WDM where each bands can be operated with different wavelength. The transmission speed of optical fiber is very high.

A lightpath must be established between any pair of nodes before data can be transferred. The Routing and Wavelength Assignment (RWA) algorithms are used to select the best routes and assign wavelengths to the established connections. Since there is a limited number of a wavelength available on fiber link and wavelength-continuity constraint, the RWA problem faces a major challenge to achieve good network performance. In this paper, we study and analyze the issues, concepts and techniques of existing RWA algorithm s in WDM optical networks.

Key Words: Routing and Wavelength Assignment(RWA), Genetic Algorithm(GA), Particle Swarm optimization (PSO), Ant Colony optimization (ACO).

1. Introduction

Wavelength Division Multiplexing (WDM) Technology has mainly been systemized to fulfil the dire need on bandwidth telecommunication networks, namely, *Wide-Area Transport Networks*. WBM networks are operated for transferring huge of low bit rate streams (Fig1.1). Furthermore, the function of a WDM network layer still grieves from technological and management problems. On the contrary, optical networks are anticipated to face a broad range of services with plethora of demands such as, *bit rate, connection (session) duration, frequency of use, and set up time*. In this regard, it becomes mandate to construct the flexible all-optical networks that permits dynamic resources sharing between different users and clients in an economical way. Moreover, Optical Network imparts ultrahigh speed transmitting, routing and transferring of data in the optical domain, having exhibited the pellucidity of data formats and protocols which strengthensthe function of network flexibility.

Thus, WDM networks normally offer “permanent" channels that can only manually reconfigured or even absolutely be static. In this scenario, researches and explorations have been executed focusing at the optimal design and dimensioning of a WDM layer for receiving the stable traffic requirements, which comprise of many Static Routing and *Wavelength Assignment (Static RWA)* issues.

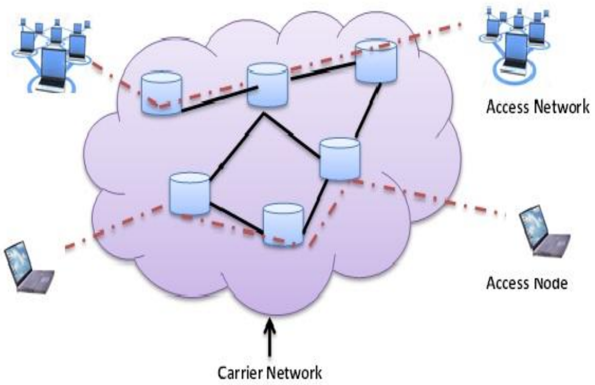

Fig. 1.1: Routing in WDM Network

Normally, the focused aim of such a task is to reduce the required number of wavelengths or fibres in the network, or to exhibit required development, having adopted Wavelength Converters. In this regard, the above stated apprehensions and the audit of dynamic network behaviour for WDM networks become indispensable. It is further discerned that this research should be associated with static planning and dimensioning tasks. It is accorded that such a comprehensive approach permits togain a network solution that is optimal, and not only for the static requirements having taken the planning phase; but also for the optimization of the network. In the present literature, endeavour has been initiatedto trace the *Dynamic Routing in WDM networks (often also called Dynamic RWA).*

2. Related Works

The auxiliary papers Ref. [1] formulate many references with regard towavelength conversion to achieve for a static and dynamic track conditions. In the same way, the article Ref. [2] elucidates wavelength conversion technologies and many analytical methods to appraise the performance and benefits of wavelength converters. Similarly, an approach is indicated in Ref. [3] to increase upper bounds for plethora of static and dynamic RWA algorithms. The influence of wavelength converters on the networks such as, ***SLE and DLE*** is the main focus of Ref. [4].

Resource Allocation, otherwise known as, *Constrained-Resource Scheduling*, makes an endeavour to change project tasks. As a result, the minimum number of resources can be efficiently used to face an obligatory extension of the project to a minimum. Due to this practical utilization, resource allocation problems have been scrupulously researched in the field of construction. In this regard, the techniques, such as, ***Integer Programming, Branch-and –Bound, Linear Programming, or Dynamic Programming*** have effectively been used to solve the problems with mathematical models.

In this regard, as Mathematical methods, are not computationally manageable for actual-life project, which is affordable in size, have resulted them to be impractical. As a result, many heuristic methods and attempts have been initiated to resolve the problem of ***Combinatorial Explosion***. However, as the heuristic models are problem dependent, rules of thumb are not able to be equally applied to all construction cases and they in addition, do not offer an optimum solution.

In this scenario, *Resource Allocation* has not been mainly examined; having taken energy efficiency aspects and, this problem has reachedan epitome status, asthe energy consumption is ruled by the WDM/OCDM due to the massive amount of passive network elements. The associated works have indicated the systematic use of resource allocation and optimization algorithms to stimulate the access network. However, these problems have not been largely studied, having analyzed routed WDM/OCDM networks.

Presently, researches have indicated that the use of resource allocation and optimization of algorithms such as ***Local Search, Simulated Annealing, GA, Particle Swarm optimization (PSO), Ant Colony optimization (ACO) and Game Theory*** to formulate the transmitted power, bit rate variation and the number of active users in order to escalate the combined throughput of the optical networks. However, the intricacy and the bias in the applications, having been presented so far have to be uplifted. Plenty of architectures and application areas have been notified in the literature where in most of the facets rely on the implementation of a *WDM Transport Layer*.

The complexities having been associate with *Resource Allocation* are mainly depended on the optimization problems, which have obviously been traced in many facets such as, ***Load Distribution, Computer Scheduling and Production Planning****[5]*.

It also becomes ardours to resolve this class of problems directly *[6-8]*.

Plenty of methods for solving resource allocation problems have been stated in the literature *[5,9]*. As a result, these methods usually utilize graph search approaches and exemplify the exponential computational complexities. Presently, ***Genetic Algorithms*** have been mostly identified as search algorithms in various applications and have afforded satisfactory performance.

3. Optimization Algorithm

The focused goal of an Optimization Algorithm is to trace a global desired solution, having resolved all the required problems, otherwise known as ***Objective Functions***. In this regard, Global Optimization search schemes are further segregated into two main domains namely, ***Deterministic and Probabilistic***.

In Deterministic Search schemes, there is anonly way to proceed from present execution step to another step.

Deterministic Algorithms also receive the similar output (results) for the same Algorithmic Inputs. The principal drawback of Deterministic Algorithms like, ‘Divide and conquer’ is that they become computationally upscale even with regard toaverage optimization issues [10].

On the contrary, in *Probabilistic Search schemes*, there is only one than one way to move from the present execution step to another step. As a result, ***Random Numbers*** can be adopted to know the way forward towards the next execution step. This randomization enriches the probabilistic algorithms to figure out certain issues much rapid, having been contrasted to Deterministic Algorithms [11].

In segregation, these issues are being rectified in terms of the environment in which, they are being evolved. They can broadly be fragmented into two categories, ***Static and Dynamic***.

A static optimization issue is commonly traced, by its immediate problem shooting techniques by which, its status remains stable, until the particular search is over the problem space. On the contrary, the status of a dynamic optimization problem is constantly getting changed due to its series of events [12].

Evolutionary Algorithms (EA) are commonly known as, ***Generic Meta-Heuristic Optimization Algorithms*** [13], in which, the resolution to an issuedesperately depends on a particular time.

However, ***Swarm Intelligence (SI)*** algorithms are rooted at the ***Population Based Evolutionary Algorithms, or Social Learning Behaviour of the Species***. The practical areas of SI schemes areenormous in the multi disciplines of Science and Industry such as, *Communication Networks,* Biomedical, *Combinatorial Optimization, Electronics and Electromagnetic, Graphics and Visualization, Prediction, Neural Networks, Robots, Scheduling and Signal Processing.*

3.1. Swarm Based Technique

Traditional Mathematical Optimization Techniques such as,***Integer Linear Programming (ILP), Graph Colouring etc***, have depended on very feeble for determining *NP-Hard Optimization* relatedissues. The required power, computational time, hinders them increatingbetter solutions in an ideal environment because of the time fluctuation.

In this regard, ***Swarm Intelligence Algorithms*** are generally known as, ***Heuristic Search Methods***, which determine the metaphor of natural biological evolution and/or the social behaviour of species [14].

In SI algorithms, a 'swarm' becomes a compilation of non-sophisticated members whose, collaboration with others execute complex tasks [15]. In this scenario, ***Ant Colony Optimization (ACO),*** Genetic ***Algorithms (GA) and Particle Swarm Optimization (PSO)*** are some popular and very fortunate swarm intelligence based evolutionary optimization algorithms. However, there are plethora of applications based on the principles having its root on Swarm Intelligence. It is further being underscored in Ref. [14, 16].

3.1.1. Ant Colony Optimization (ACO)

Having been reinforced by well-knitted trait of ants in a colony to track the nearest path between their nest and a source of food, ACO Algorithm has been well nurtured by ***Dorigo et al.****[17, 18]*. ACO is a population based algorithm, which comprises a collection of mobile agents called, ants. Each member of the population corresponds with others through a domain in anequalled fashion by laying and following pheromone trails. This idiosyncratic facet of cooperation between the ants is called stigmergy, which guides the ants to trace the nearest path between food source and destination.

3.1.2. Genetic Algorithm (GA)

Having been motivated by the natural/biological evolution facets of a species [15] like, ***Reproduction, Crossover, Selection and Survival of the Fittest*** Genetic Algorithm, an evolutionary search scheme has been developed. A genetic algorithm is a population based algorithm in which each *member of the population (swarm)* is being known as, a '***Chromosome'.*** Every chromosome expresses a solution to the problem, having been notified by a candidate. *Genetic Algorithm* begins enabling all the chromosomes in the population. In a single iteration, a set of new chromosomes are formed, having inculcated the next generation of swarm members. In this process, current members of the population get operated by the facets like, ***'Crossover' and 'Mutation'***. In this context, a fitness function has been initiated to quantize the aspect of solution, having been indicated by each chromosome.

The chromosomes with indigent fitness value, which is below a certain limit, have been exempted from the next generation and this process ceaselessly remains until either the whole swarm changes or till the allotted number of iterations is completed.

3.1.3. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO), an evolutionary, population based, optimization algorithm inspired by animal social behaviour such as, A flock of birds or a school of fish [16], has initially been invented by ***Kennedy and Eberhart****[19]*.

PSO paves a way for the simple and local interactions, which in a way leads to complex global behaviours. It is further accorded that each member of the population (swarm) in a PSO algorithm, is called a ***Particle***, which comprises of position and velocity. Velocity in a way, transforms a position of a particle to the next stage.

PSO Algorithms commence having stimulated all the particles in the swarm. The particle with the ideal fitness value in the swarm has been intimated as the ***'Globally Best Particle'*** where as the particle with the significant value in each neighbourhood is notified as the '***Locally-Best Particle'***. The swarms are further classified into sub-swarms called, ***Local Neighbourhoods.***

Thus, new velocity is calculated based on either the positions of the Globally-Best or Locally-Best particles in a single iteration. Further, the same velocity has been applied to the particle.

3.2. Comparison between Different Swarm Algorithms

The PSO concept has successfully been used to clear up many industrial and engineering optimization problems in the diversified areas such as, *Biomedical, Communication Networks, Prediction, Neural Network, Graphics and Visualization, Signal Processing, Electronics, Antenna Design, Modelling, Fuzzy and Neuro-Fuzzy Logic, Prediction and Forecasting, Scheduling andRobotics.* [20]

Furthermore, PSO makes a comprehensive analysis of publications on the application of PSO in fields of Engineering and Technology. Some of the pros of using PSO Algorithm are as follows:

- A novel concept.
- An ideal implementation of a problem search algorithm.
- Consists of lesser algorithmic parameters to adjust than other evolutionary algorithm like, ***Genetic Algorithms***.
- Lucid in terms of Controlling Parameters.
- Computationally feasible.

Many comparative studies have been initiated to study the efficacy of PSO with other evolutionary algorithms. GA and PSO are almost sameas both techniques are mainly devoted to ***Population-Based Search Schemes*** that mimic the natural biological evolution and/or the social behaviour of species [14,21].

One improvement of PSO over GA is that PSO is more computationally adoptable [21]. In this context, *Mouser and Dunn* [22] culminate that PSO is not only offering the best results of quality, having been compared with GA, but also becoming ease to configure. There are less algorithmic parameters in PSO compared to other Swarm Intelligence Based Algorithms. In GA, the fitness function contributes the member of the population who stay and exclude in the next generation. This process demands a subtle design of the fitness function. No selection of operation based fitness function is available in PSO. As a result, each member of the population aims at the best solution through an iterative process.

In Ref. [14] a performance comparison has been executed between different swarm intelligence algorithms by constant optimization test problems. It culminates that PSO Method has been traced better than other algorithms in terms of *Solution, Quality and Success Rates*. Moreover, PSO functions better compared to GA and ACO in terms of computation time. One demerit of ACO with regard to PSO is its low convergence towards optimal/near-optimal solution.

On the contrary, no pheromone table in PSO has to be regulated for next move decision-making. In Ref. [23] and [24], evolutionary algorithms mainly systematize for extraction and segregation. *The study also ends that PSO functions ideal than ACO Algorithms.* Performance Comparison and the research between PSO and other evolutionary schemes have also been highlighted in Ref.[22, 23].

4. Conclusion

It can bededuced that the resource allocation problems are 0-1 programming problems and becomes complex to solve directly when the numbers of resources are enormous. Plenty of methods such as, ***Dynamic Programming, Separable Convex Objective Functions, and Graph Theory*** have been applied to track the affordable solutions for this sort of issue. Nowadays, Genetic Algorithms have often been instituted in resolving the issues. Moreover, ***Genetic Algorithms or, Evolutionary Algorithms*** are commonly being identified as search algorithms, which implement the mechanism of natural selection to offer the best solution to candidates.

Optimization Method, based on the Heuristic PSO Approach allures because of its performance, lucidness, novelty, which inculcate matrix inversion, mainly numerical procedures and other Heuristic approaches. The trait of ***Particle Swarm Optimization (PSO)*** is also adorable like, ***Genetics Algorithms (GA).*** The allotment of resources, having optimized PSO strategy permits and formulates transmitted power and OCPs satisfying QoS and energy efficiency constraint. In achieving the network optimization, a novel model has been elucidated; In pursuit of this study, a comprehensive numerical results for identifying the reliable and acceptable solutions are revealed, having considered the realistic networks operation.

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