# Aircraft Maintenance Routing Using Artificial Intelligence Based Approach

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# Declaration

I certify that this research work titled "*Aircraft Maintenance Routing Using Artificial Intelligence Based Optimization Approach"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged / referred.

Ali Babar

2013-NUST-MS-Mts-078

# Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Dr. Khurram Kamal

(Supervisor)

# Copyright Statement

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I am thankful to my Creator my God to have guided me throughout this work at every step and for every new thought, which You setup in my mind to improve it. Indeed I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual was Your will, so indeed none be worthy of praise but You.

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*I specially dedicate this work to my most respectable parents, caring wife and lovely children whose tremendous patience, support and cooperation enabled me to achieve this landmark.*

# Abstract

Aircraft maintenance is one of the critical aspect that ensures safe and optimized operations of an airline. In order to get maintenance at regular intervals as per the FAA regulations, an aircraft is required to be routed towards a maintenance station. Aircraft maintenance routing is one of the major factor that influences the decisions throughout the airline operations. Considerable efforts has been made in recent past focusing on the aircraft routing and its optimization, whenever an aircraft is due for maintenance.

Given a balance and periodic flight schedule air craft maintenance routing is about finding the most suitable route for an aircraft in order to achieve the minimum cost for that route. A good rotation plan of an aircraft must be cost-effective and should allow each aircraft in a fleet to undergo maintenance checks.

In this research, the main aim remained to provide complete formulation that can find a balanced route for an aircraft that belongs to a particular fleet of an airline. Given a set of flight legs for a specific aircraft type with the specified maintenance locations and known remaining flying hours a search based routing model is proposed which optimizes the aircraft maintenance routes. The objective of this research is to minimize the maintenance cost, and multiple optimization techniques has been evaluated in order to obtain the best objective results.

**Key Words:** *Aircraft, Aircraft maintenance routing, optimization, Moth Flame Optimization, Particle Swarm Optimization. Dragon Fly Optimization, Genetic Algorithm, Breadth First search, Dijkstra's algorithm*

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# CHAPTER – 1

# INTRODUCTION

## 1.1 Overview

Airline sector runs on very high operational costs, strict protocols and complex scheduling process. One of the main factor influencing these factors is aircraft maintenance. Large airline networks usually have multiple fleets of aircrafts and hundreds of destinations. In order to achieve the full operational capacity an aircraft have to go through preventive maintenance procedures. As per rules outlined by Federal Aviation Authority an aircraft has to undergo a type maintenance check periodically.

Initially an airline creates a schedule of flights that are dependent on the arrival and departure times. These schedules are prepared keeping in view the past travelling history, passengers demand and future forecast. Airline schedule is the main product of any airline that is being sold. After scheduling for origin and destinations, fleet assignment is carried out. Typically a fleet consists of aircrafts with similar parameters, characteristics and operational performance. These fleets are based on the aircraft model, seating capacity and maintenance requirements for example fleet of Boeing 737, Fokker, and Cessna etc. Fleets are then assigned to flight schedule network based on the travelling, load and distance requirements of particular zone. After fleet assignment, aircrafts are assigned to pre generated flights / routes based on their tail number. While these assignments are made, maintenance constraints required by FAA are deliberated. The assignment of route to an aircraft while considering its maintenance requirements is called "**Aircraft Maintenance Routing Problem**". Aircraft maintenance routing is one of the challenging and importance aspect for an airline for its critical and efficient operations.

As per the rules of Federal Aviation Authority there are four type of checks and maintenances that every airline has to follow. These checks varies in scope, duration and frequency. These checks are categorized as [1]:-

- Type A check (after every 65 – 125 hours) Duration is almost 8 hours
- Type B Check (after 300-600 hours). Duration is almost 1-3 days
- Type C Check and Type D check (after 1-4 years)

Aircraft maintenance is comprised of multiple checks. The re-occurrence of these checks is very dependent on combination of flight take off / landing cycles, flight hours, number of days after maintenance [2]. These checks can be performed at any airport or maintenance station which is capable of handling maintenance of that particular type of aircraft and have capacity to accommodate multiple number of aircrafts. Industry practices are much stricter than FAA requirements. Most airlines follow a much stricter rule that allows at most 35 to 40 flying hours before an operational aircraft go through its transit check [3].

Although maximum of the maintenance checks are carried out at night, the focus is always about where the aircraft is going to spend its night each day in a cyclic schedule. A cyclic schedule can be of a day, a week or whole month. There are numerous approaches being used for construction of aircraft maintenance route in a cyclic schedule. These approaches can be categorized as String, Big cycle and one day routes. The String model is all about constructing the flight routes, which spans between visits to maintenance stations. This type of model is considered as maintenance feasible and covers all aircrafts of a single fleet. The Big Cycle model includes every scheduled flight and identifies one single route covering multiple days. This type of cycle, schedules maintenance visits at defined intervals throughout [4].

The one-day route model is designed based on assumptions that previous day has disrupted the maintenance planning for aircraft. Airline, as an industry functions in multidimensional scenario, where many accidental or unscheduled events force them to adjust already scheduled plans and reroute the aircrafts. These unseen or unexpected events can be severe weather disruptions, equipment failure, route diversions, unplanned maintenance demands from FAA or aircraft manufacturer etc. Based on the assumptions aircraft routing can be carried out in two stages. In first stage, planning of one-day routes in carried out in such a way that each route ensures aircraft maintenance feasibility. This can be attained by generating adequate number of routes that ends at a maintenance station. In the second stage, every aircraft is assigned to that route. This stage is executed every night before the airline starts its operations [5].

The one-day routing model is different from string and big cycle models because it construct flight routes with duration of a single day. The one-day route planning model is used throughout this research. This approach generates routes that are maintenance feasible and these routes are terminated at selected maintenance stations, these maintenance feasible routes are then allocated to aircraft, which is due for maintenance. A maintenance critical aircraft is the one which has crossed its threshold of legal current flying hours and now is termed as high time aircraft. Now this aircraft has to reach the maintenance station with in its cushion time, because after that, if aircraft crosses its legal remaining flying hours than it cannot fly without maintenance.

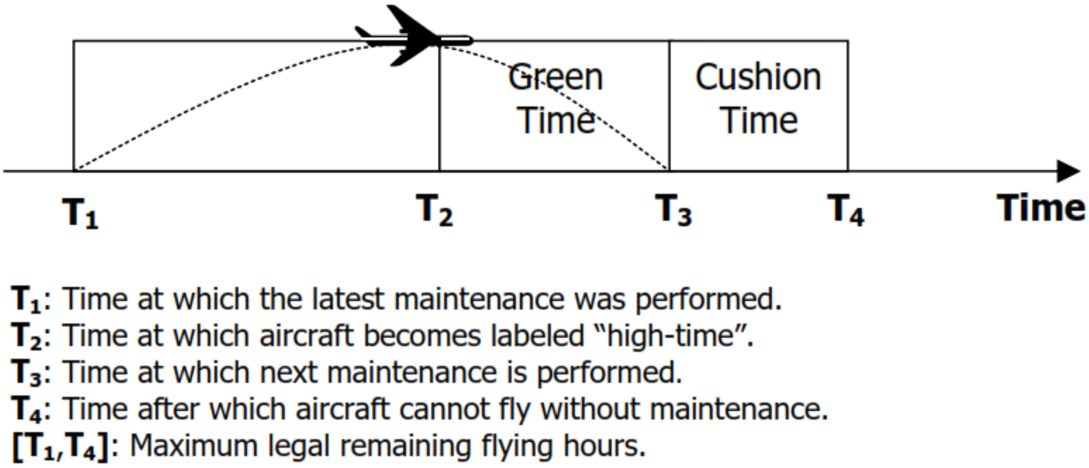


Figure 1. Time limit definition for an aircraft [6]

Flight schedules of an airline are represented as flight leg-networks, in this type of network nodes symbolizes cities, whereas, arcs between these cities or nodes symbolizes the flight legs, which joins cities. However, a realistic problem with this type of timeline representation is about keeping in line with the departure time and arrival time of each arc. During course of this research we have used a connection network as presented by Sarac et al.[6].

## 1.2 Motivation

In a dynamic operational environment, airlines try to keep themselves ahead by reacting to the unscheduled and unseen changes in such a manner that their daily operations runs un-interrupted. Most of the time keeping up to these changes is proved to be challenging, because the complex route planning is carried out in advance, whereas unexpected events might occur daily and disrupt the planned routes / schedules. On the other hand, airline personnel are left with a challenge of daily adjusting the long-term plans by fitting in the daily operational requirements posed by those unseen events.

Over a period of years multiple techniques and approaches has been put forth by several researchers to identify the exact problems being faced during the aircraft maintenance rotation. These approaches has been proposed to model aircraft maintenance routing, while keeping in view the constraints and factors that are affecting the planning. But the complexity of problem that is caused because of the huge number of variables and constraints, directly affects the aircraft routing, hence the proposed solutions are unable to exactly formulate a model that can cater for the complete aircraft maintenance rotation problem. During the recent past, the aircraft rotation has been formulated using the depth first search algorithm and particle swarm optimization based approaches has been used to optimize the aircraft rotation problem

## 1.3 Research Methodology

- **Research proposal** of using AI based algorithms for optimization of aircraft maintenance routing was initiated.
- **Literature Review** was carried by incorporating / exploring following resources:-
  - Interaction with technical specialists linked with the aircraft maintenance.
  - Consulting recommended books on aircraft maintenance routing.
  - Reading research articles on Aircraft maintenance routing problem and its optimization.
- **Dataset Collection**
  - Aircraft flight schedules for two different airlines named Delta Airline and United Airline were obtained from American Bureau of Transportation Statistics under United States Department of Transportation.
- **Algorithm development and Implementation Stage**
  - An algorithm was formulated for aircraft maintenance routing using breadth first search and Dijkstra’s algorithm to get feasible routes.
  - Moth Flame Optimization Algorithm, Particle Swarm optimization algorithm were used to optimize the formulated objective function.
  - Devised algorithms were then implemented in MATLAB using optimization toolbox and tested on acquired dataset.

## 1.4 Thesis Organization

This study is organized in seven chapters. Chapter 2 covers the brief history and previous work about aircraft maintenance routing and its optimization. In chapter 3, theory behind the routing and proposed methodology for generation of feasible maintenance routes is discussed. Chapter 4 summarizes the tools and techniques used for the formulation of proposed methodology. The details of simulations / experiments and their results are contained in chapter 5. Different graphs and tabular data are also depicted in the same part. Chapter 6 provide the detailed analysis of the results and discuss the outcomes of all the tools and techniques used. Concluding remarks along with future work is encompassed in last chapter that is chapter 7.

## 1.5 Summary

This chapter describes:

- Airline sector runs on very high operational cost, strict rule & regulations and complex scheduling processes. Maintenance constraints and requirements of an aircraft plays a havoc in case of already scheduled flight routes.
- An airline prepares a flight schedule, one year prior to the real time operations. These schedules are then published and sold as main product. After that airline assigns a fleet of aircraft and finally aircraft routing based on individual tail number is carried out.
- Aircraft maintenance routes are generated based on string, big cycle or one day routing model. These routes are then optimized to get the best feasible solution so as to minimize the maintenance cost.

# CHAPTER 2

# LITERATURE REVIEW

This chapter provides the overview of airline industry, different techniques methods and algorithms being used for aircraft scheduling, aircraft maintenance routing, aircraft maintenance cost calculations and aircraft maintenance route optimization.

## 2.1 Airline Industry

For the past thirty years airline industry has been growing steadily, benefiting from demand driven by the growing economy along with technological advancement that took the overall flying experience to a new level [7]. Although 9/11 temporarily interrupted the growth, but it did not had long lasting effect. The statistical data in Fig. 2.1 reveals that the annual gross output of the air transportation industry had doubled over the decade.

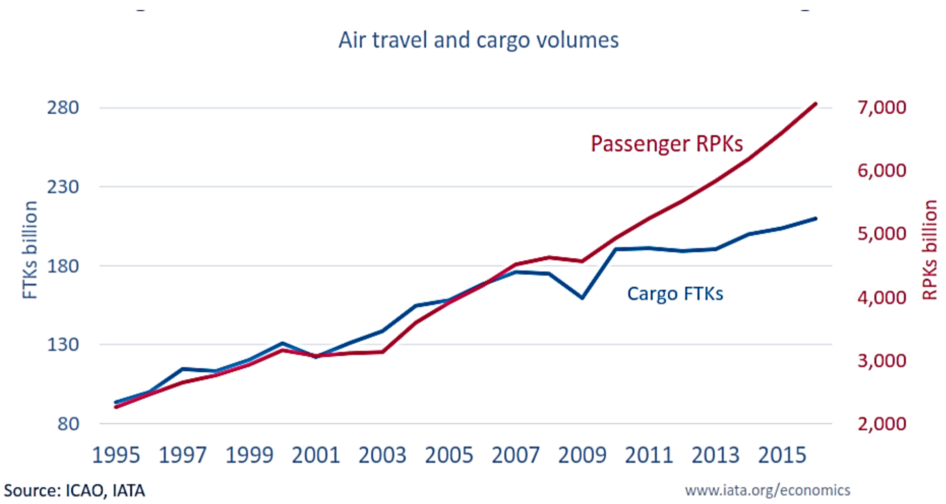


**Figure 2.1.** Air travel and cargo volumes [8]

## 2.2 Aircraft Routing Problem

The airline scheduling is the most crucial part in operational management of any airline, and a major share of the profit attained in this industry can be credited to the strong and efficient planning. The scheduling process begins twelve months in advance before the commencement of operations, and the final schedule of an individual aircraft and crew is fixed a few weeks before implementation. Due to the in-built complexity of the airline scheduling problem, a small size airline scheduling model may also get unmanageable using direct solution methodologies. Therefore, the complete decision making process can be sub divided into 04 phases that are frequently solved in a sequential manner. These four phases includes schedule planning, fleet assignment, aircraft routing, and crew scheduling [9]. The product of this phased process includes timetable for flights, aircraft assignment and crew assignment, so that both can cover planned flights, while fulfilling the respective requirements.

### 2.2.1 Problem Overview

Aircraft maintenance can be divided in to two categories, namely scheduled maintenance and unscheduled maintenance as depicted in figure 2.2. Aircraft Routing Problem (ARP) deals with both of them.

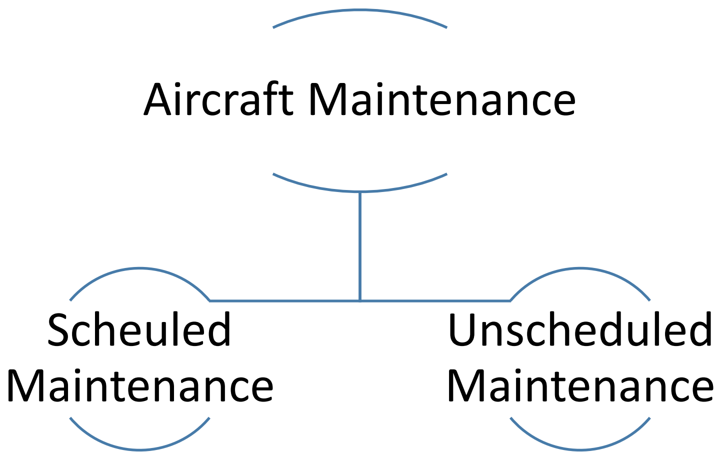


**Figure 2.2.** Aircraft Maintenance Categories

ARP defines the flight route or flight sequence in such a manner that each specific type of aircraft is assigned to every flight leg for a certain time period while it fulfils various maintenance requirements mandated by FAA. As discussed earlier, and aircraft has to go through four types of maintenance checks namely type 'A', type 'B', type 'C' and type 'D'. Type 'A' check is a routine visual inspection of major systems and is conducted after 65 hours of flight, while type 'B' check is carried out every 300 to 600 of flight hours, and includes a complete visual inspection and a thorough lubrication of all moving parts. Whereas, type C and type D checks take multiple weeks, these two type of checks are usually planned at a higher level and are not part of daily operations [10].

The main objective of ARP revolves around minimization of the total cost associated with maintenance checks while assigning individual aircraft to a particular route. As Clark et al [11] proposed that the tail number assignment of an aircraft can gain a benefit of thorough value, whereas, penalty for undesired connections can also be imposed on a route. He proposed that when passengers on an aircraft do not need to change their plane between immediate stations, then a negative cost or a thorough value cost can be imposed. Extra revenues can also be generated by removing changeovers as staying on the same aircraft is a motivation for passengers which subsequently generates extra revenues.

Every maintenance activity bears its own maintenance cost, this cost also depends on periodicity of maintenance, whether that type maintenance is carried out too soon, or too close to, the maximum flying hours. Labour man hours and resources are wasted if early maintenance is carried out and causes frequent maintenance operations, whereas, the maintenance delayed maintenance that is close to maximum flying hours reduces flexibility in routing. It is worth mentioning that the objective function proposed for the aircraft rotation problem differs according to the weightage of the model, and it is not necessary that it include all the costs discussed above. ARP is often taken in to account as a feasibility problem (e.g., Gopalan and Talluri (1998)) [3]. Same approach has been used in this research having focus on determining maintenance-feasible routes for aircraft.

During the past few decades “Aircraft Maintenance Routing Problem” has attained substantial consideration in the academic literature. It is pertinent to highlight that in tactical model solving, aircraft routing problem is typically resolved months before the commencement of scheduled flights. It produces a cyclic schedule that repeats periodically. Hence, it is presumed that same sequence of light legs will be covered by each aircraft periodically. Therefore, most of the time, the initial aircraft locations and the initially accumulated flying hours are disregarded. But on the contrary in operational model, that is during operations the initial locations as well as the exact values of the initial flying hours are explicitly catered for.

In the coming paragraphs we will review the tactical & operational model and its related literature.

### 2.2.2 Tactical Model

The initial investigation on tactical aircraft maintenance routing problem was carried out by Kabbani and Patty (1992) [12]. For route identification of a maintenance feasible aircraft they proposed a set-partitioning model. In their research a maintenance feasible route is the one in which an aircraft is grounded overnight in a maintenance station after every three days. A two-step solution was developed by them, which builds over-the-day routes in the first step and then in second steps it connects them to construct the routes. Clarke et al. (1997) [11] investigated the aircraft rotation problem and proposed an objective, in which profit is maximized by building an optimal route for each aircraft under certain maintenance and operational restrictions. They compared both aircraft rotation problem and asymmetric travelling salesman problem and developed a mathematical programming formulation.

Talluri (1998) [13] presented an algorithm based on polynomial-time solution which ensure four day maintenance routing and produces a solution in which an aircraft visits a maintenance station every four days. He shows that the problem is NP-complete. Gopalan and Talluri (1998) [14] studied the aircraft maintenance problem as a three-day routing problem. Authors presented a polynomial-time algorithm, that while considering different maintenance constraints can find finds aircraft routes. In their paper, they considered both static infinite-horizon and dynamic finite-horizon. Barnhart et al. (1998) [15] studied a string-based model with maximum aircraft utilization constraint for the aircraft routing problem. The objective of their research was assignment fo aircraft maintenance feasible routes while minimizing the total cost that incurs during assignment. They developed a branch-and-price approach to solve their presented model. Mark and Boland (2000) [16] formulated the aircraft maintenance routing problem as an asymmetric traveling salesman problem with replenishment arcs. A heuristics method using simulated annealing based approach was proposed to find the upper bounds and a Lagrangian dual problem using a sub gradient optimization method to find lower bounds. Sriram and Haghani (2003) [1] proposed the scheduling problem for a domestic flight schedule based on one-week planning horizon.

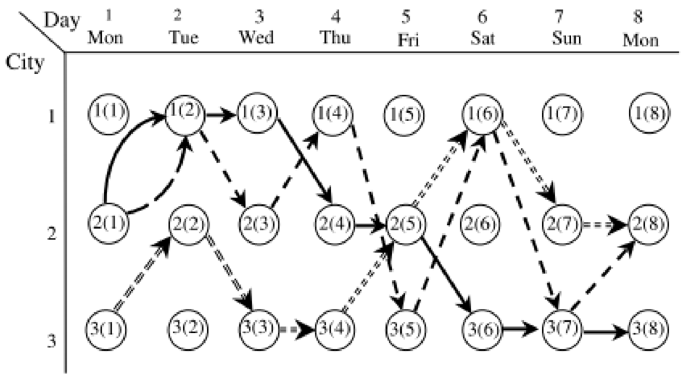


**Figure 2.3** City-Day network with 7-day planning horizon [1]

In their study, they considered both Type A and B maintenance checks, since the planning horizon was short, therefore, introduction of the type B check was not efficient. They developed heuristic procedure with an objective to minimize the cost, which was calculated by adding the total cost of Type A and Type B maintenance checks while the penalty for assigning unsuitable flight leg to an aircraft was also added.

A two-step heuristic approach maximizing the aircraft utilization was proposed by Afsar et al. (2006) [17]. A rolling-horizon framework for ten weeks, with one week sliding window was proposed. Liang et al. (2011) [18] formulated the model as a network flow problem with the objective of maximizing the through values and penalizing short connections. For daily AMRP an innovative compact-network representation of the time and space network was proposed. Later, Liang and Chaovalitwongse (2013) [19] proposed a network based mixed integer linear programming model and generalized their previously proposed compact model and proposed a new model based on weekly rotation-tour network. Haouari et al. (2013) [20] presented an alternative RLT-based compact construction of the aircraft maintenance routing problem. They addressed the case where each aircraft visits a maintenance stations before reaching the specified maximum flying time, maximum number of take offs and specified maximum number of days, and proved that general purpose solvers can be used to solve large instances.

### 2.2.3 Operational Model

Keeping forgone in view with respect to the tactical aircraft maintenance routing problems, the related literature is relatively scarce. Sarac et al. (2006) [6] studies the problem as a daily operation problem rather than addressing it in long-term planning. They presented mathematical formulation for minimizing the unused legal flying hours while adjusting resource availability constraints. They proposed a branch-and-price approach to solve it. Orhan et al. (2012) [21] developed an integer linear goal-programming model with the objective to minimize the legal flying hours of the aircraft before they undergo maintenance. It is noteworthy that both Sarac et al. (2006) [6] and Orhan et al. (2012) [21] considered a single-day planning horizon. Basdere and Bilge (2014) [22] while studying the operational aircraft maintenance routing problem considered both the un-capacitated and the capacitated variants. To minimize the unused legal flying hours they proposed a multi-commodity flow model for a critical aircraft by modifying the connection network so that it would be able to track the used flying time of each aircraft. To check whether a connection arc was flown before or after maintenance they duplicated the arcs. Moreover, a simulated annealing heuristic for the OAMRP was also described in their research. It is worth highlighting that

Basdere and Bilge (2014) [22] supposed during the planning horizon of an aircraft, the particular aircraft can undergo maintenance only once.

### 2.2.4 Integrated Models with Aircraft Routing

Up till now we have studied the models that deals with aircraft maintenance routing problem as a standalone problem, however, there are multiple number of aircraft routing models that involve integration of fleet assignment and crew pairing with the aircraft routing models. Figure 2.4 describes in detail about the integrated airline scheduling and dependency of aircraft maintenance routing on other scheduling factors.

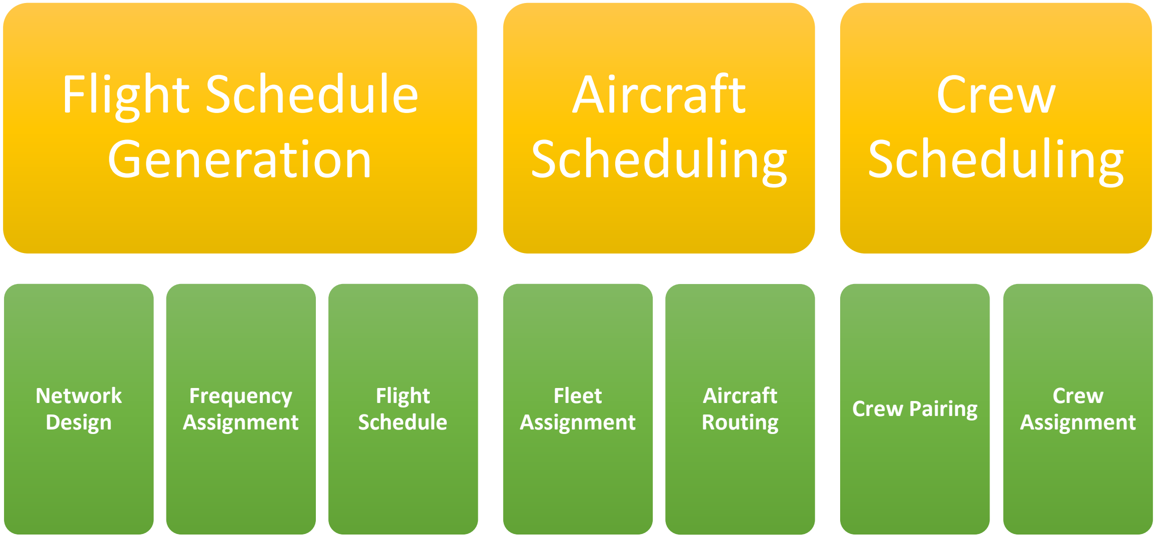


**Figure 2.4** Overall airline scheduling process

#### 2.2.4.1 Integrated Aircraft Routing with Fleet Assignment

The decision stage of aircraft routing has apparently interdependency on fleet assignment, therefore, Barnhart et al. (1998) [15] introduced the flight string model so as to keep the synergy of integrating these two stages. In his model, a string is defined as a sequence of flights which are connected and they originates and terminates at maintenance stations, such that the flights are flow-balanced and fulfils the maintenance requirements. Since such types of model contains millions of strings for a moderate-size flight schedule, the authors proposed a branch-and-price method to handle it.

The input for the fleet assignment model is comprised of a schedule of flight routs, a fleet (set of aircrafts), the operational cost of the fleet, minimum turn-around time and maintenance requirements for different fleets. After processing available aircraft is assigned to different flight legs as output. Negative cost of thorough flight (Clarke et al., 1997) [11] is additionally assigned as passengers prefer to continue journey on without changing an aircraft, moreover, opportunity cost caused by the overbooking is also included in the objective function. The aircraft routing model find the cost that is minimum for aircraft routing while keeping in line, the constraints of flight coverage, fleet count, and maintenance requirements.

### 2.2.4.2 Integrated Aircraft Routing with Crew Scheduling

The crew cost is another factor that influences the cost and increase the expenditures of an airline company. Crew limitations involve strict limits on total flight time, number of landings and total working hours. In routine flights a crew group cannot change aircraft for two continuous short connected flights, and this factor affects the decision of aircraft routing. Therefore, Cohn and Barnhart (2003) [23] are the first one to introduce a basic integrated model that combines the string based maintenance with partition based crew pairing model. However, two major disadvantages of this integrated model were its weak LP relaxation and large size, which in turn inhibited its use in real problems. In their paper, the authors focused on solution procedures that guarantee a maintenance-feasible crew pairing solution while considering a small number of maintenance routing constraints.

Mercier et al. (2005) [24] also proposed an integrated model of aircraft routing and crew scheduling by further extending the model proposed by Cordeau et al. (2001) [25], while combining additional features. They developed a tighter model formulation and introduced several improvements in the solution. The authors also benchmarked their results with respect to those of Cohn and Barnhart (2003) [23], by presenting improved performance.

In their follow-on research, Mercier and Soumis (2007) [26] improved their existing model that combines the crew scheduling problem and aircraft routing problem. Keeping forgone in view, integrating aircraft routing with crew pairing can get significant results instead of solving these two problems sequentially. In this paper, the authors considered flexible departure times for each leg, i.e., they allowed the departure times to slightly deviate from the original schedule. As demonstrated by their results, cautiously selected departure times can impact aircraft routings and crew pairing in a beneficent manner.

### 2.2.5 Operational Aircraft Maintenance Planning

Considering the estimates, stated by the industry of aeronautics, the range of maintenance activities is from 10% to 20% of an airlines direct operating costs that depends upon the fleet age, size and usage [36].

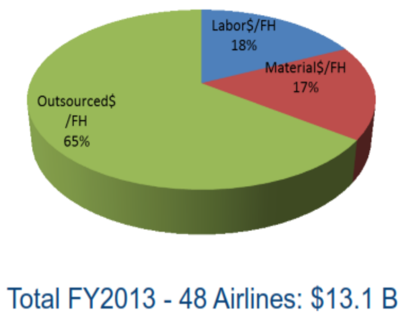


**Figure 2.5** Direct maintenance cost by element [37]

Over the last two decades the influence of maintenance cost on the average operating cost has increased significantly. Serviceable aircraft is considered as the major operational requirement for any airline, whereas, occurrence of unscheduled maintenance can cause exorbitant delays and may cause cancellation, which in result can affect the cost, unless unserviceability is repaired or rectified in time. The trade-off between aircrafts operational reliability and operational risk is always considered as complex, and priorities of an airlines policy may vary according to it. Serviceability and operational ability of an aircraft is considered as its ability to meet the operational requirements in terms of reliability, operational risk, maintenance and operational costs. The trade-off between them is very complex and priorities may vary a lot with respect to the airlines policy.

Sherali et al. [38] presented the current improvements in methods and models that are being developed for the integrated model of fleet assignment problem and maintenance activities. Clark et al. [39] and [40], presented an overview of management sciences and operations research, including fleet scheduling and maintenance routing. Dijkstra et al. [41] with the use of mathematical models and approximation techniques investigated a capacity-planning problem of the aircraft maintenance personnel. Moudani et al. (2000) [42], discussed an arrangement of a dynamic programming approach with a heuristic technique to solve the FA problem with maintenance schedule problem.

### 2.2.6 Tabular Overview of Published Research

Some of the research published for aircraft maintenance routing and its integration with Flight scheduling and fleet assignment are listed below in table 2.1.

| Author | Year | Flight Scheduling | Fleet Assignment | Aircraft Routing |
|---|---|---|---|---|
| Nayla Ahmed et al. | 2016 | | | X |
| Gürkan, H et al. | 2016 | X | X | X |
| Malek Sarhani et al. | 2016 | | | X |
| Gavranis, A et al | 2015 | | X | X |
| Omar Ezzinbi et al. | 2014 | | | X |
| M. Basdere et al. | 2014 | | | X |
| Maher S.j et al. | 2014 | | | X |
| Liang et al. | 2013 | | X | X |
| Haouari et al. | 2013 | | | |
| Díaz et al. | 2012 | X | X | |
| Arikan et al. | 2012 | X | | |
| Orhan et al. | 2012 | | | X |
| Liang et al. | 2011 | | | |
| Sherali et al. | 2010 | X | X | |
| Gao et al. | 2009 | | X | X |
| Burke et al. | 2009 | X | | X |
| Nitika & Pal | 2007 | X | X | |
| Gao & Johnson | 2007 | | X | X |
| Papadakos | 2006 | | X | X |
| Sandhu & Klabjan | 2006 | | X | X |
| Afsar et al. | 2006 | X | | X |
| Sarac et al | 2006 | | | X |
| Barnhart et al. | 2006 | X | | X |
| Huisman et al. | 2004 | | | X |
| Klabjan et al. | 2002 | | | X |
| Stojkovic & | 2001 | X | | X |

| | | | | |
|---|---|---|---|---|
| Soumis | | | | |
| Cordeu et al. | 2001 | | | X |
| Haase et al. | 2001 | | | X |
| Moudani et al. | 2000 | | X | |
| Barnhart et al. | 1998 | | | X |
| Barnhart et al | 1998 | | X | X |
| Talluri, K.T | 1998 | | | X |
| Gopalan, R et al. | 1998 | | | X |

**Table 2.1** Research published for integrated AMR problem

### 2.2.7 Aircraft Disruption Recovery

Another aspect of aircraft maintenance routing is about the disruption recovery. It deals with minimizing maintenance cost and maximizing the profit. Some studies related to this area is found in the literature. Initially the study related to aircraft disruption recovery was considered as aircraft recovery studies. Earlier research includes Teodorovic et al. (1984) [27], Jarrah et al. (1993) [28], Cao and Kanafani (2000) [29]. Main motivation of their research were certain areas which deals with the disruption recovery of an aircraft, this includes minimizing the number of cancelled flights, minimize number of aircrafts required for recovery and minimizing customer delays. The current research in disruption recovery is about formulating models, which integrates crew and aircraft recovery together.

### 2.2.8 Optimization of Aircraft Maintenance Routing

Very less research has been carried out in this area, most of the initial studies were about the problem formulation. Metaheuristics has been used to solve the aircraft maintenance routing problems. As formulated by Basdere and Bilge [22] compressed annealing metaheuristics can be used to solve the problem and to get feasible routes for individual aircraft. Metaheuristics have been used for the optimization of the preventive AMR which is an NP-hard problem. Quan et al. (2007) [30] proposed GA (genetic algorithm) to be used in order to solve the preventive maintenance scheduling problem. The authors presumed that due to the random nature of failure rate, the exact methods are not adapted for the preventive maintenance. Furthermore, Chiu et al. (2004) [31] also used genetic algorithm to build an aircraft maintenance support system. Yang and Yang (2012) [32] established a

GA based optimization model for Aircraft Maintenance based on minimization of the objective function.

Particle swarm optimization was used by Ezzinbi et al. [33], to solve the proposed model and then compared it to the genetic algorithm. Sarhani et al. (2016) [34] extended the model proposed by Sarac et al. [11] for the AMR problem and added the case of aircraft on the ground (AOG) situation which is caused by the unscheduled maintenance events. Following table 2.2 summarizes the research work carried out using optimization for AMR problems.

| Author | Year | Optimization Technique |
| --- | --- | --- |
| Chiu et al. | 2004 | Genetic Algorithm (GA) |
| Quan et al. | 2007 | Genetic Algorithm (GA) |
| Yang and Yang | 2012 | Genetic algorithm (GA) |
| Basdere and Bilge | 2014 | Integer linear programming with compressed annealing |
| Ezzinbi et al. | 2014 | Particle Swarm optimization |
| Sarhani et al. | 2016 | Particle Swarm optimization with mutation operator |
| Al-Thani et al. | 2016 | Mixed Integer Programming model with VLNS heuristics |

**Table 2.2** Optimization techniques used for AMR

Keeping in view table 2.2, we can safely assume that very less research has been carried out for the optimization of Aircraft Maintenance Routing Problem. This has become the integral part of our research and whole thesis is focused on getting the optimized route for an aircraft while maintaining the constraints.

## 2.3 Scope and Objectives of Research Work

### 2.3.1 Scope

Keeping foregone in view, the available data and opportunities in the field of aircraft maintenance routing, the envisaged scope of this study is as under:-

- To formulate mathematical model that aims at minimizing the cost of aircraft maintenance routing while ensuring the flight and maintenance constraints.
- Make use of latest search based algorithms and optimization algorithms to generate efficient routes that can ensure high aircraft utilization while following maintenance constraints.
- To analyse the different solutions derived from the different optimization techniques. This analysis will be based on the obtained heuristic results and the computational time for each algorithm based on predefined data sets.

### 2.3.2 Objectives

Following objectives were earmarked and aimed to be achieved during the course of this study:-

- Produce efficient routes for an aircraft.
- Investigate a currently available state of art technique for maintenance route generation
- Optimization of generated routes for best fleet efficiency.

To achieve these objectives, following activities are required to be performed

- Obtain real aircraft scheduling dataset for a commercial airline
- Formulate and develop an objective function that can minimize the aircraft maintenance cost keeping in view:
    - Minimization of unused flying hours
    - Check maintenance constraints
        - Maintenance slots
        - Maintenance man hours
- Apply AI based optimization techniques to get the efficient routes
- Compare different optimization techniques and perform analysis on results obtained

# CHAPTER – 3

# PROPOSED METHODOLOGY

## 3.1 Problem Formulation

In this section, understanding of the network structure will become the basis of forming the mathematical formulation, hence we will start from understanding it. All the notations used are summarized in Table 3.1 for reference. The aircraft maintenance routing problem is generally modelled as cyclic or closed loop network. It uses Origin Destination schedule as input with integer restrictions on the variables. In this formulation each aircraft represents an isolated entity.

| Parameters | Description |
|---|---|
| i | Index, that specifies the number of flight legs |
| j | Index, that specifies the number of routes |
| m | Index, that specifies the number of maintenance types |
| k | Index of aircraft |
| s | Index of overnight stations |
| A | Set of connection arcs formed |
| $R_k$ | Set of feasible routes generated from BFS |
| N | Set of flight legs obtained from data source of United Airlines |
| M | Set of maintenance stations obtained from data source of United Airlines |
| $S_m$ | Set of overnight stations where maintenance can be performed. Random data |
| K | Set of aircrafts obtained from UA data |
| $c_j^k$ | The cost for selecting the route ‘j’ for aircraft ‘k’ |
| $\tau_k$ | Remaining flying hours of aircraft ‘k’. |
| $a_m^k$ | Man-hours needed to perform maintenance for selected aircraft ‘k’. Randomly assigned |
| $b_m^k$ | If aircraft needs maintenance type ‘m’ it is ‘1’, else ‘0’ |
| $d_{js}^k$ | It is ‘1’ if route ‘j’ of aircraft ‘k’ end at overnight station ‘s’, else ‘0’ |
| $\lambda_{is}$ | Set as ‘1’ if the arrival city of flight leg ‘i’ is overnight station s, else ‘0’ |
| $\gamma_{ji}^k$ | Set as ‘1’ if the route ‘j’ of aircraft ‘k’ contains flight leg i, else ‘0’ |
| $L_{ms}$ | Defines availability of man hours for maintenance ‘m’ |
| $Z_{ms}$ | Defines number of available slots for maintenance |
| $y_j^k$ | Decision variable is set as ‘1’ if the route ‘j’ of aircraft ‘k’ is selected, else it is ‘0’ |

**Table 3.1** Summary of notations used in mathematical formulation

## 3.2 Flight Network Structure

Published schedules of any airline are conventionally represented as networks of flight legs. In these type of flight network the nodes are identified as cities and the arcs between those nodes / cities are identified as flight legs that connect those cities. A major issue pertaining to this type of flight leg network representation is about handling the arrival time and departure time for each arc of network. In order to overcome this problem, a connection network can be formed, in which nodes can represent flight legs whereas, arcs can represent suitable connections among the flight legs. This type of connection network specifies that, the departure city of a node j, is same as the arrival city of node i, and this means that an arc (i,j) between node (flight leg) i and node (flight leg) j is available, moreover, the turn-around time of an aircraft and arrival time of flight leg i, is less than or equal to the departure time of flight leg j. In simpler words, it can be said that if an aircraft can successively fly a flight leg i, j and arc (i,j) then arc (i,j) already do exist.

In this research, set portioning based formulation, as presented by Sarac et al. [6] is used. The decision variable represents the possible routes for an aircraft. This method has been selected because of multiple reasons. First one is that this method can easily combine constraints that are based on availability of routes and it emphases on assignment of realistic routes to the aircraft. This type of formulation has been very effective in case of general vehicle routing problems as presented by Barnhart et al. 1998 [15], Desrosiers et al.1984 [43] and Dumas et al. 1991 [44]

The cost coefficients, $c_j^k$ is linked with the routes (decision variable) and represents the cushion time for the aircraft (Figure 1). All the cost coefficient related to route will become zero if the selected aircraft is not due for maintenance or is not a high time aircraft. However, if aircraft k is due for maintenance and is a high-time aircraft, then $c_j^k$ will be equal to the remaining flying hours (legal) of selected aircraft 'k', minus the duration of the next selected route j.

$$c_j^k = \text{Remaining legal flying hours} - \text{Next route flying hours} \qquad (3.1)$$

It is also worth noting that the selection of next route is based on remaining flying hours such that the constraint (remaining flying hours) for route R*k* is catered for. $y_j^k$ is the decision variable and it represent a feasible route, it will be '1' if the feasible route is selected and '0' otherwise. Moreover, four types of constraints formulate this problem, there are: aircraft coverage (3.3), flight leg coverage (3.4), man-hour availability (3.5), and slot availability (3.6). The mathematical formulation can be written as:

$$\min \sum_{k \epsilon K} \sum_{j \epsilon Rk} c_j^k \, y_j^k \qquad (3.2)$$

Subject to:

$$\sum_{j \epsilon Rk} y_j^k = 1 \qquad \forall\, k \in K \qquad (3.3)$$

$$\sum_{k \in K} \sum_{j \in Rk} \gamma_{ji}^k \, y_j^k = 1 \qquad \forall\, i \in N \qquad (3.4)$$

$$\sum_{k \in K} \sum_{j \in Rk} a_m^k \, d_{js}^k \, y_j^k \le L_{ms} \qquad \forall\, m \in M \text{ and } s \in S_m \qquad (3.5)$$

$$\sum_{k \in K} \sum_{j \in Rk} b_m^k \, d_{js}^k \, y_j^k \le Z_{ms} \qquad \forall\, m \in M \text{ and } s \in S_m \qquad (3.6)$$

$$y_j^k \in \{0,1\} \qquad \forall\, k \in K \text{ and } j \in R_k$$

Based on the above given equations we can further formulate our equation to cater for the unscheduled maintenance requirements. Papakostas et al. (36) formulated the cost of unscheduled maintenance based on linear combination of scheduled and unscheduled maintenance probability. Sarhani [34] applied this probability and formulated the mathematical model as:

$$\min \sum_{k \epsilon K} \sum_{j \epsilon Rk} c_j^k (1 + \beta_k) \, y_j^k \qquad (3.7)$$

Subject to:

$$\sum_{k \in K} \sum_{j \in Rk} (1 + \beta_m^k) a_m^k \, d_{js}^k \, y_j^k \le L_{ms} \qquad \forall\, m \in M \text{ and } s \in S_m \qquad (3.8)$$

$$\sum_{k \in K} \sum_{j \in Rk} (1 + \beta_s^k) \, b_m^k \, d_{js}^k \, y_j^k \le Z_{ms} \qquad \forall\, m \in M \text{ and } s \in S_m \qquad (3.9)$$

Whereas, the remaining constraints remains the same. The coefficients $\beta_k, \beta_m^k, \beta_s^k$ are greater than zero in case of unscheduled maintenance event, and they will be zero in case of a scheduled maintenance. Now the objective function will ensure the minimization of the cost incurred during aircraft maintenance routing and will ensure constraints 3.3, 3,4, 3.8 and 3.9.

## 3.3 Pre-processing

Data set for processing and calculation was obtained from American Bureau of Transportation Statistics under United States Department of Transportation. The pre-processing was carried out to remove needless arcs so that the structure of the connection network may be simplified. These arcs includes:-

- The nodes in the connection network, whose out degree is equal to zero
- The nodes whose in-degree is zero
- Nodes having their in degree as one
- Nodes having their out degree as one

After pre-processing a complete flight network for seven days was obtained having hub and spoke flight paths with 743 flights per week and 150 nodes. Hub and spoke networks uses airports as flight feeders, which interconnect all the fights, as compared to the direct flight networks having direct flights from origin to destination.

# CHAPTER – 4

# TOOLS & TECHNIQUES

This chapter explains the techniques used to fulfil the scopes of thesis as well as the background theory related to them.

## 4.1 Route Generation

Based on the available data from American Bureau of Transportation Statistics, multiple tables were generated having origin, destination, nodes and arcs data. Pre-processing was carried out on these data tables and finally available subsets were used for route generation. Since all the flights are cyclic in nature, that is once a flight leaves and origin it comes back to the same airport after a certain period. The scope of the problem in the research is as follows:-

- Only domestic airline operation of a major US airline is considered
- Aircraft assignment to a route is made before the maintenance scheduling
- Aircraft maintenance checks are performed during the night
- The maintenance bases are located at the airport
- Flight sequence is directed and cyclic
- Aircraft starts their flying at different airports

For the modelling purpose, a directed weighted graph has been used, that plotted the routes from each origin to destination as depicted in figure 4.1 and 4.2.

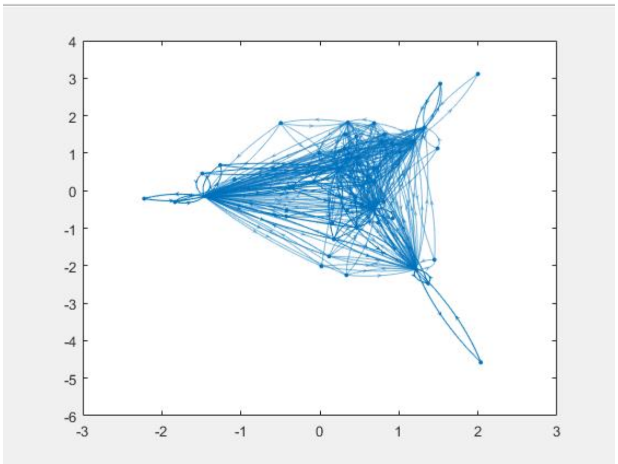

**Figure 4.1** Origin Destination plot using directed graph

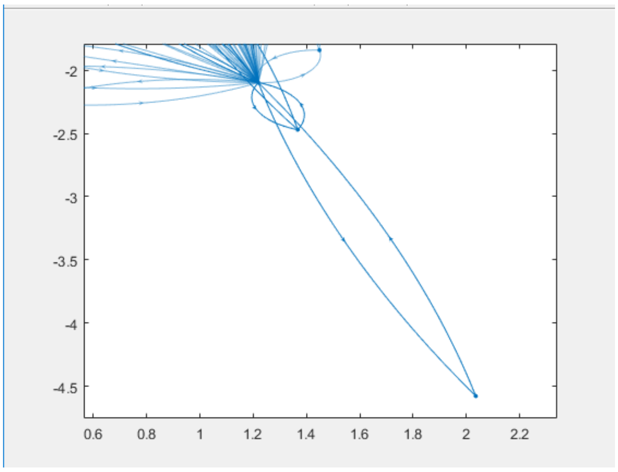


**Figure 4.2** Directed Graph (Zoom)

### 4.1.1 Breadth First Search

After construction of the directed graph, breadth first search (BFS) techniques was used to find the feasible routes from origin to destination. As compared to depth first search technique which was used by Sriram et al. [1], breadth first search is always able to find the available routes and produces the solution if its available. However, the computation time of breadth first search is much larger than depth first search.

Randomly an aircraft and a random node is chosen from the list of available nodes and aircrafts. To find all the possible cyclic schedules of the current node exhaustive breadth first search is performed. The assigned links are then removed and saved as another list. Again breadth first search is performed to find the cyclic schedules for the second aircraft, from a different selected node. This procedure is repeated until all the aircrafts has been assigned to all the flight paths. Steps for calculating all routes using BFS are listed below:-

Step 1: Generate a list of cities (nodes) in any order, then create a list of aircrafts. Initialize the iteration from 1.

Step 2: let iter=1 (iteration number)

Step 3: Pick ‘k’ aircraft such that it belongs to K and pick node ‘i’

Step 4: Check if the outgoing arcs are available, that is the number of outgoing arcs is greater than zero.

Step 5: Perform exhaustive breadth first search to discover all the destinations from the selected node. Find all the possible cyclic routes.

Step 6: Remove the selected cyclic routes from the list and save them in another list.

Step 7: Subtract 1 from the outgoing arc of the selected node.

Step 8: If number of iterations is less than the max number of iterations assigned, increment ‘n’ and go to step 3 and repeat. Otherwise stop.

The results obtained from the above mentioned procedure are depicted below in form of figure 4.3 and 4.4 respectively.

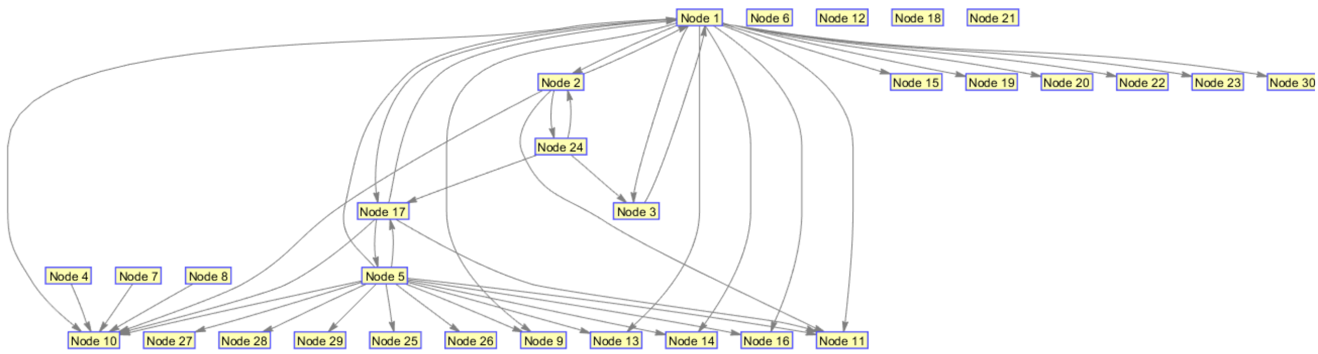


**Figure 4.3** Routes obtained from node 1 to all nodes

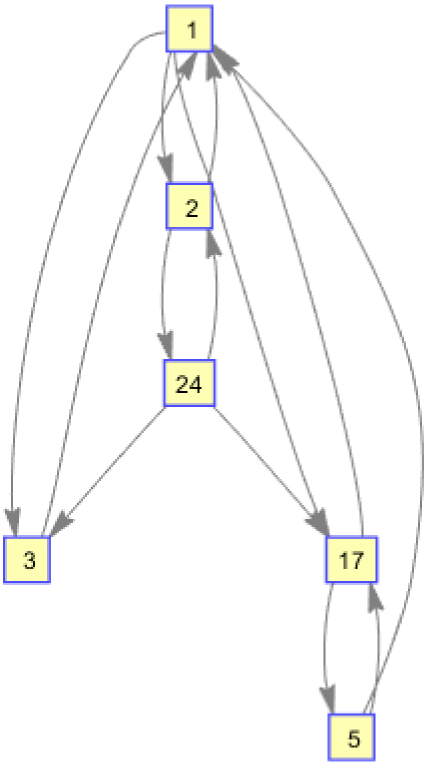


**Figure 4.4** Cyclic schedule obtained from node 1 to node 5 using BFS

### 4.1.2 Optimal Route Using Dijkstra's Algorithm

After finding all the possible routes from origin to destination, another subset of flights legs have been obtained. These flight legs are then used to obtain the most feasible route for an aircraft from its current airport to the maintenance station. However, before assigning a maintenance station S*m* to a particular aircraft, capacity limitations of an airport are to be found. Violating the capacity limitations can increase the maintenance cost by applying penalty factors on the cost calculations.

The maintenance capacity of an airport / maintenance station has some restrictions. These restrictions could be:-

- Availability of slots for maintenance so that aircraft can simultaneously undergo maintenance at that particular airport.
- Availability of main hours for that particular maintenance type that an aircraft requires to undergo at that maintenance station.

Once capacity restrictions are calculated, list of suitable maintenance stations are obtained. Now Dijkstra's algorithm is used to find the optimal path of an aircraft from its current station to all the suitable maintenance stations while keeping in view remaining flying hours constraint.

Dijkstra's algorithm was conceived by Edsger W. Dijkstra. It's an algorithm used for finding the shortest paths between nodes in a graph, which in our case is current station node and maintenance station node. The pseudo code for Dijkstra's algorithm is appended below:-

```
function Dijkstra(Graph, source):
  create list of vertex Di
  for each vertex v in Graph:
      find dist[v] ← INFINITY        // find unknown distance from current position to v
      Check prev[v] ← UNDEFINED      // Check if previous node has optimal path
      add v to Q
     dist[source] ← 0                       // Distance from source

   while Q is not empty:
 u ← vertex in Q with min dist[u]    // First select the node with min distance
       remove u from Q
          for each neighbour v of u:          // where v is still in Q.
         alt ← dist[u] + length(u, v)
         if alt < dist[v]:             // A shorter path to v has been found
             dist[v] ← alt
             prev[v] ← u

     return dist[], prev[]
```

Steps used to find the most feasible route from current station to the feasible maintenance station are listed below:-

Step 0: Make list of maintenance stations with their capacity handling data

Step 1: Check every maintenance station one by one for slots and man-hours availability

Step 2: Formulate a list of all feasible maintenance stations that do not affect the maintenance cost.

Step 3: Verify the current flying hours of aircraft. If greater that longest available route, mark that aircraft as high time aircraft (Figure 1)

Step 4: Use Dijkstra's algorithm to find the shortest route from current station to the randomly selected maintenance station.

Step 5: Check if the remaining flying hours are equal to zero.

Step 6: If zero, then remove the arc from the list of arcs and save as selected route else

Step 7: Remove route and save the route as feasible route

Step 8: Go to step 6 and continue, unless unused flying hours = 0, or number of available routes=0.

Step 9: Subtract all the selected route hours from remaining flying hours and select the minimum of un used flying hours.

Step 10: Remove the route permanently from the list of arcs and replenish the list of arcs with remaining ones.

Step 11: Repeat from step 4 and find the unused flying hours for all the maintenance stations

Step 12: Select the maintenance station with minimum unused flying hours. Remove the maintenance station from the list

Step 13: Repeat from step 0 to find most feasible route for the next aircraft due for maintenance.

## 4.2 Optimization

Once the objective function was formulated using the equation given in 3.7. We apply different optimization techniques in order to find the best heuristic values. In this research we have used particle swarm optimization technique as used by Omar Ezzinbi et al. [33] and Sarhani et al. [34], Moth Flame Optimization Technique as proposed by Seyedali Mirjalili (2015) [45], Dragon Fly Optimization Algorithm as proposed by Seyedali Mirjalili (2015)

[49] and Genetic Algorithm. All optimization algorithms are discussed in subsequent paragraphs.

Optimization is the process of finding the best possible solution, for a given problem. Over the last few decades the complexity of problem increased and the requirements for new optimization techniques became more obvious. Initially before the formulation of heuristic optimization techniques, mathematical optimization techniques were used for optimizing problems. The mathematical methods are mostly deterministic and they have one major insufficiency that is local optima entrapment. Then genetic algorithm was proposed and after years of its proposal highest attention to such algorithms was given.

### 4.2.1 Particle Swarm Optimization (PSO)

Particle swarm optimization is a meta-heuristic evolutionary approach proposed by Kennedy and Eberhart in 1995 [46]. The individual agents forms swarm and are called particles. They are represented by vectors, whereas, each particle represents a potential solution of the optimization problem. In PSO each particle has two vectors namely the velocity vector and the position vector. The particles are updated according to their previous best position and furthermore, swarm is updated according to previous best position of the entire swarm. Block diagram of PSO algorithm is depicted below for reference.

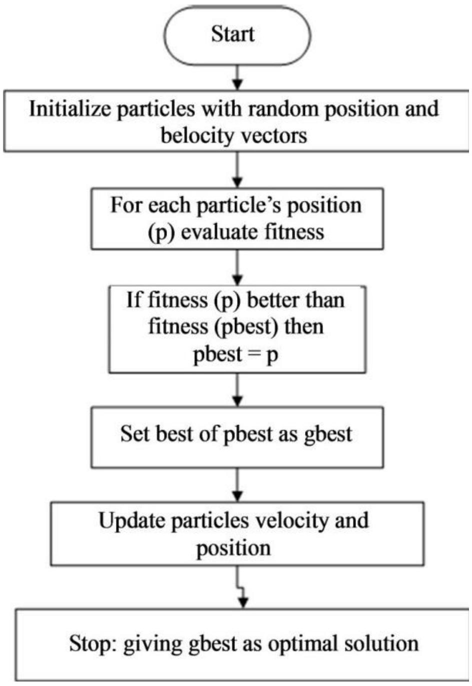


**Figure 4.5** Block diagram of PSO

## 4.2.2 MOTH FLAME OPTIMIZATION (MFO)

Moth Flame optimization algorithm gained its inspiration from the natural navigation behaviour of Moths. An interesting behaviour of moths is their special navigation methods that they use in night. Flying pattern of Moths has evolved by flying in night while using the moon light as their destination. They use traverse orientation method for navigation purpose. Traverse orientation is the most effective method of travelling for a long distance in a straight line. When a moth flies, it maintains a fixed angle from the moon, and thus attains a straight path towards the destination [48]. Fig. 4.6 shows a model of transverse orientation opted by moths. Since the moon is extremely far away from the moth, this navigation method guarantees flight in a straight line.

However, despite the fact that transverse orientation is very effective, it has been observed that moths flies displays spiral flying behaviour around the lights. Practically, moths cannot identify artificial light display such behaviour. When moths see an artificial light, they try to maintain an angle with the light so that they can fly in straight line, which outcomes in spiral movement.

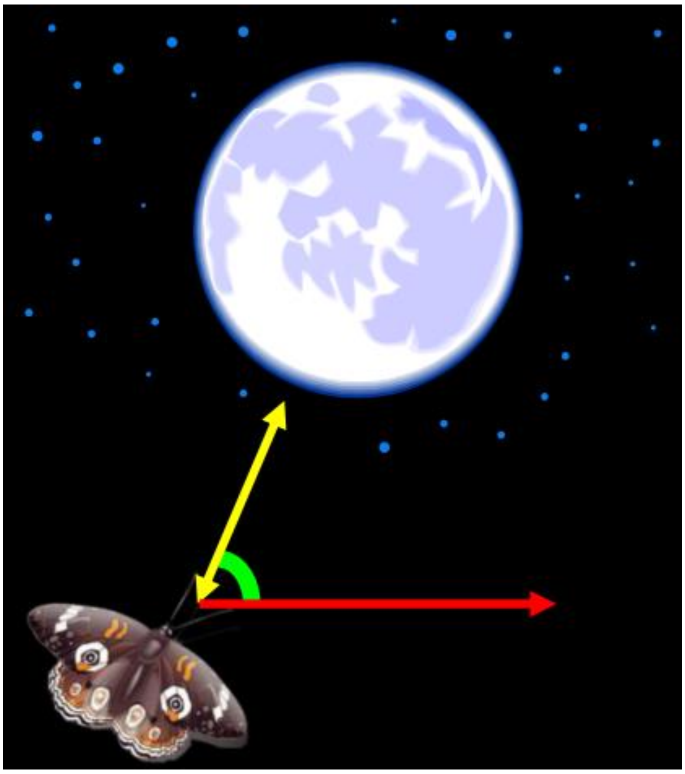

**Figure 4.6** Traverse orientation of a moth with respect to moon light

The Moth Flame Optimization algorithm assumes that moths are the candidate solutions, and positions of moths in space are the problem variables. Hence, the moths can fly in single dimension, two dimension, three dimension or hyper dimension space, meanwhile changing their positions. MFO is a population-based algorithm, therefore, the sets of moths are represented in form of matrix, whereas, the fitness value is the return value of the objective function for each moth [47].

### 4.2.3 Dragonfly Optimization Algorithm

Naturally dragon flies display behaviour of static and dynamic swarming, and this behaviour became the source of inspiration for this optimization algorithm, as proposed by Seyedali Mirjalili (2015) [49]. Dragonflies belongs to the family of small predators are, who hunt for all types of small insects. A type of dragon fly named as Nymph dragonflies feed on small fishes and marine insects as well. Dragon flies displays unique swarming features, their swarming behaviour is based on two basic purposes, that are hunting and migration. Hunting / feeding falls in the category of static swarming, whereas, migration is type of dynamic swarming. While hunting (static swarm), dragonflies fly backward and forward over a small area (in groups) in order to hunt on other flying insects [50]. However, during migration (dynamic swarms) a maximum number of dragon flies forms a swarm and start migrating for a long distance, in one direction.

Dynamic and static swarming behaviour of dragon flies are same as the two main phases of meta heuristic optimization, those are exploration and exploitation. Survival of swarm is dependent on their behaviour, where, all the individuals in the swarm move towards the feed and move outwards in case of enemy attack. On the basis of these two behaviour, position updating is affected by five main factors, same are depicted in figure 4.7

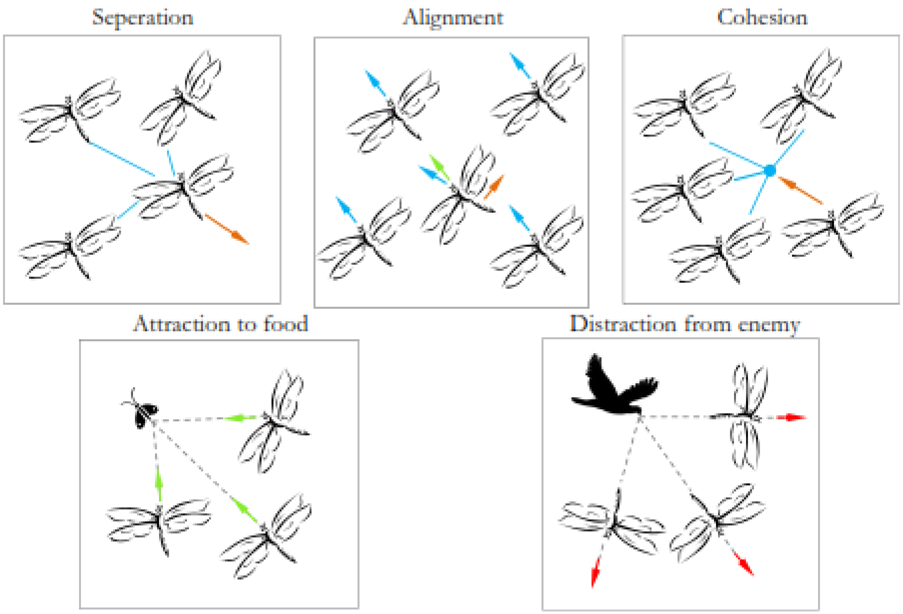


**Figure 4.7** Corrective pattern of individuals in swarm [49]

The pseudo code for dragonfly algorithm is appended in coming paragraphs:

Initialize the dragon flies populations

Initialize step vectors

While the end condition is not satisfied

Calculate the objective values of all dragon flies

Update the food source and enemy

Update alignment, cohesion, food and enemy factor

Calculate separation, alignment, cohesion, attraction and distraction

Update neighbouring radius

If a dragonfly has at least one neighbouring dragonfly

Update velocity vector

Update position vector

Else

Update position vector

Endif

Check and correct the new positions based on boundary limits of variables

End While

### 4.2.4 GENETIC ALGORITHM (GA)

In a genetic algorithm, a better solution is obtained by evolving the population of candidate solutions. A set of properties can be mutated and altered for every candidate solution. It an iterative process in which the fitness of every individual which belongs to a population is evaluated, whereas, the evolution starts from a population of randomly generated individuals. Like other optimization algorithms, the fitness of GA is usually the value of the objective function in the optimization problem being solved. The more fit individuals are selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. After it reaches a maximum number of generations or achieves a satisfactory fitness level, the algorithm terminates itself.

# CHAPTER - 5
# EXPERIMENTATION & RESULTS

## 5.1 Experimental Parameters

The dataset used for simulation was obtained from American Bureau of Transportation Statistics under United States Department of Transportation. It's worth highlighting that all the researchers have used instances generated by different software like CPLEX, instead of using the original flight network data. Some of the researchers that were sponsored by airlines have used their original dataset, but due to the confidentiality reasons they have not published it. In this research flight network data of Delta Airlines which containing 61533 flights, with 150 airports and 743 origin and destinations is used. Complete data was tested for 25 aircrafts covering 743 flight legs. Formulation of objective function and implementation of all four optimization algorithms was done using MATLAB R16. In order to run the simulations 32 test problems were taken, based on the available data of Delta Airlines. Data used for testing purpose is tabulated below: -

| Case No | No of Cities | OD Pairs | Critical Aircraft | Remaining Flying Hours | Remaining Flying Minutes | Iterations |
|---|---|---|---|---|---|---|
| 1 | 150 | 743 | 1 | 6 | 360 | 5 |
| 2 | 150 | 743 | 1 | 7 | 420 | 5 |
| 3 | 150 | 743 | 1 | 8 | 480 | 5 |
| 4 | 150 | 743 | 1 | 9 | 540 | 5 |
| 5 | 150 | 743 | 1 | 10 | 600 | 5 |
| 6 | 150 | 743 | 1 | 12 | 720 | 5 |
| 7 | 150 | 743 | 1 | 15 | 900 | 5 |
| 8 | 150 | 743 | 3 | 6 | 360 | 10 |
| 9 | 150 | 743 | 3 | 7 | 420 | 10 |
| 10 | 150 | 743 | 3 | 8 | 480 | 10 |
| 11 | 150 | 743 | 3 | 9 | 540 | 10 |
| 12 | 150 | 743 | 3 | 10 | 600 | 10 |
| 13 | 150 | 743 | 3 | 12 | 720 | 10 |
| 14 | 150 | 743 | 3 | 15 | 900 | 10 |
| 15 | 150 | 743 | 5 | 6 | 360 | 10 |
| 16 | 150 | 743 | 5 | 7 | 420 | 10 |
| 17 | 150 | 743 | 5 | 8 | 480 | 10 |
| 18 | 150 | 743 | 5 | 9 | 540 | 10 |
| 19 | 150 | 743 | 5 | 10 | 600 | 10 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 20 | 150 | 743 | 5 | 12 | 720 | 10 |
| 21 | 150 | 743 | 5 | 15 | 900 | 10 |
| 22 | 150 | 743 | 10 | 10 | 600 | 10 |
| 23 | 150 | 743 | 10 | 12 | 720 | 10 |
| 24 | 150 | 743 | 10 | 15 | 900 | 10 |
| 25 | 150 | 743 | 15 | 6 | 360 | 10 |
| 26 | 150 | 743 | 15 | 15 | 900 | 10 |
| 27 | 150 | 743 | 18 | 6 | 360 | 10 |
| 28 | 150 | 743 | 18 | 15 | 900 | 10 |
| 29 | 150 | 743 | 20 | 6 | 360 | 10 |
| 30 | 150 | 743 | 20 | 15 | 900 | 10 |
| 31 | 150 | 743 | 25 | 6 | 360 | 10 |
| 32 | 150 | 743 | 25 | 15 | 900 | 10 |

**Table 5.1** Dataset used for experimentation.

## 5.2 Results of Implemented Algorithm

Based on the given set, all the four optimization algorithms were applied. Simulation was carried out on an Intel Core i5 CPU @1.7 GHz and 4 GB memory. For each test case Turnaround Time (TAT) of 50 minutes was taken. The first applied algorithm is MFO (Moth flame optimization), then PSO (Particle swarm optimization), DFA (Dragon fly algorithm) and GA (Genetic algorithm). In the end Number of Lost Flight Opportunities (NLFO) was calculated for each algorithm. NLFO defines the average number of wasted flight opportunities due to the unused remaining flying hours [22]. Simulation results are given below in form of table, complete table displays all test cases with results for each optimization algorithm applied.

| Case No. | Algorithm | Best Score with TAT (hrs) | Without TAT (hrs) | Execution Time (s) | NLFO |
|---|---|---|---|---|---|
| **Case 1** | MFO | 0.85 | 0.01 | 35.082 | 0.17 |
| | PSO | 0.833 | 0 | 50.683 | 0.1667 |
| | DFA | 0.8393 | 0.005 | 46.035 | 0.1679 |
| | GA | 0.8554 | 0.022 | 153.501 | 0.1711 |

| Case No. | Algorithm | Best Score with TAT (hrs) | Without TAT (hrs) | Execution Time (s) | NLFO |
|---|---|---|---|---|---|
| **Case 2** | MFO | 0.8667 | 0.033367 | 55.7 | 0.1733 |
| | PSO | 0.8333 | 0 | 62.512 | 0.1667 |
| | DFA | 0.8334 | 0 | 53.202 | 0.1667 |
| | GA | 0.8618 | 0.028467 | 71.421 | 0.1724 |
| **Case 3** | MFO | 0.8333 | 0 | 37.691 | 0.1667 |
| | PSO | 0.8333 | 0 | 67.495 | 0.1667 |
| | DFA | 0.8372 | 0.003867 | 47.546 | 0.1674 |
| | GA | 0.838 | 0.004667 | 70.454 | 0.1676 |
| **Case 4** | MFO | 0.8667 | 0.033367 | 37.526 | 0.1733 |
| | PSO | 0.836 | 0.002667 | 36.286 | 0.1672 |
| | DFA | 0.836 | 0.00267 | 36.286 | 0.1673 |
| | GA | 0.8333 | 0 | 72.647 | 0.1667 |
| **Case 5** | MFO | 0.9167 | 0.083367 | 36.286 | 0.1833 |
| | PSO | 0.834 | 0.000667 | 61.097 | 0.1668 |
| | DFA | 0.8445 | 0.011167 | 35.469 | 0.1689 |
| | GA | 0.8524 | 0.019067 | 74.21 | 0.1705 |
| **Case 6** | MFO | 0.85 | 0.016667 | 35.855 | 0.17 |
| | PSO | 0.8372 | 0.003867 | 84.544 | 0.1674 |
| | DFA | 0.8375 | 0.004167 | 34.616 | 0.1675 |
| | GA | 0.8379 | 0.004567 | 71.721 | 0.1676 |
| **Case 7** | MFO | 0.8333 | 0 | 46.038 | 0.1667 |
| | PSO | 0.8346 | 0.001267 | 78.604 | 0.1669 |
| | DFA | 0.85 | 0.016667 | 38.564 | 0.17 |
| | GA | 0.8577 | 0.024367 | 70.966 | 0.1715 |
| **Case 8** | MFO | 2.5778 | 0.077801 | 196.486 | 0.5156 |
| | PSO | 2.5604 | 0.060401 | 233.576 | 0.5121 |
| | DFA | 2.5593 | 0.059301 | 241.727 | 0.5119 |
| | GA | 2.6255 | 0.125501 | 251.029 | 0.5251 |
| **Case 9** | MFO | 2.5393 | 0.039301 | 292.752 | 0.5079 |
| | PSO | 2.5007 | 0.000701 | 351.516 | 0.5001 |
| | DFA | 2.5585 | 0.058501 | 252.674 | 0.5117 |
| | GA | 2.5378 | 0.037801 | 245.455 | 0.5076 |
| **Case 10** | MFO | 2.55 | 0.050001 | 168.053 | 0.51 |
| | PSO | 2.6167 | 0.116701 | 399.589 | 0.5233 |
| | DFA | 2.5473 | 0.047301 | 223.841 | 0.5095 |
| | GA | 2.7632 | 0.263201 | 243.531 | 0.5526 |
| **Case 11** | MFO | 2.6514 | 0.151401 | 151.184 | 0.5303 |
| | PSO | 2.8167 | 0.316701 | 287.022 | 0.5633 |
| | DFA | 2.6412 | 0.141201 | 215.489 | 0.5282 |
| | GA | 2.5735 | 0.073501 | 238.182 | 0.5147 |
| **Case 12** | MFO | 2.6 | 0.100001 | 442.644 | 0.52 |
| | PSO | 2.9489 | 0.448901 | 303.955 | 0.5898 |
| | DFA | 2.6009 | 0.100901 | 212.132 | 0.5202 |
| | GA | 2.6445 | 0.144501 | 238.182 | 0.5289 |
| **Case 13** | MFO | 2.5568 | 0.056801 | 392.673 | 0.5114 |
| | PSO | 2.7877 | 0.287701 | 385.514 | 0.5575 |

| | | | | | |
|---|---|---|---|---|---|
| | DFA | 3.0518 | 0.551801 | 221.923 | 0.6104 |
| | GA | 2.6898 | 0.189801 | 251.081 | 0.538 |
| **Case 14** | MFO | 2.5817 | 0.081701 | 324.473 | 0.5163 |
| | PSO | 2.8568 | 0.356801 | 389.578 | 0.5714 |
| | DFA | 2.7702 | 0.270201 | 217.824 | 0.554 |
| | GA | 2.6039 | 0.103901 | 253.28 | 0.5208 |
| **Case 15** | MFO | 4.3667 | 0.200035 | 511.776 | 0.8733 |
| | PSO | 4.3708 | 0.204135 | 667.315 | 0.8742 |
| | DFA | 4.3163 | 0.149635 | 363.497 | 0.8633 |
| | GA | 4.4445 | 0.277835 | 406.657 | 0.8889 |
| **Case 16** | MFO | 4.3279 | 0.161235 | 480.289 | 0.8656 |
| | PSO | 4.3476 | 0.180935 | 577.555 | 0.8695 |
| | DFA | 4.2705 | 0.103835 | 376.176 | 0.8541 |
| | GA | 4.7715 | 0.604835 | 2255.929 | 0.9543 |
| **Case 17** | MFO | 4.3087 | 0.142035 | 435.263 | 0.8617 |
| | PSO | 4.3179 | 0.151235 | 591.976 | 0.8636 |
| | DFA | 4.4631 | 0.296435 | 371.93 | 0.8926 |
| | GA | 4.3132 | 0.146535 | 989.754 | 0.8626 |
| **Case 18** | MFO | 4.3667 | 0.200035 | 591 | 0.8733 |
| | PSO | 4.4657 | 0.299035 | 1326.851 | 0.8931 |
| | DFA | 4.4768 | 0.310135 | 354.265 | 0.8954 |
| | GA | 4.4533 | 0.286635 | 684.313 | 0.8907 |
| **Case 19** | MFO | 4.3356 | 0.168935 | 457.51 | 0.8671 |
| | PSO | 4.3631 | 0.196435 | 558.238 | 0.8726 |
| | DFA | 4.5361 | 0.369435 | 366.194 | 0.9072 |
| | GA | 4.7164 | 0.549735 | 434.725 | 0.9433 |
| **Case 20** | MFO | 4.3 | 0.133335 | 591.354 | 0.86 |
| | PSO | 4.5667 | 0.400035 | 457.69 | 0.9133 |
| | DFA | 4.3635 | 0.196835 | 409.008 | 0.8727 |
| | GA | 4.5116 | 0.344935 | 509.393 | 0.9033 |
| **Case 21** | MFO | 4.35 | 0.183335 | 411.55 | 0.87 |
| | PSO | 5.8167 | 1.650035 | 461.581 | 1.1633 |
| | DFA | 4.4396 | 0.272935 | 379.93 | 0.8879 |
| | GA | 4.9474 | 0.780735 | 500.146 | 0.9895 |
| **Case 22** | MFO | 9.0714 | 0.73807 | 983.245 | 1.8143 |
| | PSO | 9.3331 | 0.99977 | 1009.644 | 1.8666 |
| | DFA | 9.089 | 0.75567 | 687.065 | 1.8178 |
| | GA | 9.6595 | 1.32617 | 1160.601 | 1.9319 |
| **Case 23** | MFO | 9.1333 | 0.79997 | 1043.695 | 1.8267 |
| | PSO | 9.4966 | 1.16327 | 893.155 | 1.8993 |
| | DFA | 9.7135 | 1.38017 | 660.272 | 1.9427 |
| | GA | 9.1433 | 0.80997 | 808.07 | 1.8287 |
| **Case 24** | MFO | 9.2763 | 0.94297 | 1308.209 | 1.8553 |
| | PSO | 9.5717 | 1.23837 | 1161.696 | 1.9143 |
| | DFA | 9.2942 | 0.96087 | 631.563 | 1.8588 |
| | GA | 9.6143 | 1.28097 | 1090.42 | 1.9229 |
| **Case 25** | MFO | 14.3 | 1.800005 | 1386.44 | 2.86 |
| | PSO | 14.593 | 2.093005 | 1305.296 | 2.9186 |

| | | | | | |
|---|---|---|---|---|---|
| | DFA | 14.6122 | 2.112205 | 865.574 | 2.9224 |
| | GA | 16.831 | 4.331005 | 1190.269 | 3.3662 |
| **Case 26** | MFO | 14.7455 | 2.245505 | 1267.188 | 2.9491 |
| | PSO | 15.3003 | 2.800305 | 1452.789 | 3.0601 |
| | DFA | 14.4985 | 1.998505 | 936.839 | 2.8997 |
| | GA | 15.4635 | 2.963505 | 1308.91 | 3.0927 |
| **Case 27** | MFO | 14.2 | 1.700005 | 1413.839 | 2.84 |
| | PSO | 13.7833 | 1.283305 | 1543.99 | 2.7567 |
| | DFA | 16.0647 | 3.564705 | 885.566 | 3.2129 |
| | GA | 16.1432 | 3.643205 | 1264.33 | 3.2286 |
| **Case 28** | MFO | 16.8072 | 1.807206 | 2385.699 | 3.3614 |
| | PSO | 18.35 | 3.350006 | 1786.937 | 3.67 |
| | DFA | 18.8412 | 3.841206 | 1027.495 | 3.7682 |
| | GA | 18.9426 | 3.942606 | 1869.6 | 3.7885 |
| **Case 29** | MFO | 17.6 | 2.600006 | 1324.766 | 3.52 |
| | PSO | 18.4886 | 3.488606 | 1826.881 | 3.6977 |
| | DFA | 18.8968 | 3.896806 | 1076.357 | 3.7794 |
| | GA | 18.5141 | 3.514106 | 1888.5 | 3.7028 |
| **Case 30** | MFO | 20.4865 | 3.81984 | 1173.673 | 4.0973 |
| | PSO | 20.5833 | 3.91664 | 1961.84 | 4.1167 |
| | DFA | 21.0907 | 4.42404 | 1151.086 | 4.2181 |
| | GA | 21.0299 | 4.36324 | 3027.341 | 4.206 |
| **Case 31** | MFO | 20.1431 | 3.47644 | 1807.257 | 4.0286 |
| | PSO | 20.7213 | 4.05464 | 1604.122 | 4.1443 |
| | DFA | 20.5741 | 3.90744 | 1176.565 | 4.1148 |
| | GA | 21.3324 | 4.66574 | 2089.1 | 4.2665 |
| **Case 32** | MFO | 24.368 | 3.534675 | 2136.552 | 4.8736 |
| | PSO | 25.533 | 4.699675 | 2015.894 | 5.1066 |
| | DFA | 27.6333 | 10.96664 | 1307.795 | 5.5267 |
| | GA | 28.4591 | 7.625775 | 2998.4 | 5.6918 |

**Table 5.2** Simulation Results

## 5.3 Summary

This chapter can be summarized as follows: -

- Data of United Airline for domestic flights with US was obtained from American Bureau of Transportation Statistics.
- Objective function was formulated using MATLAB
- 32 test cases were generated with multiple parameters, to test the efficiency of optimization techniques.
- MFO (Moth Flame Optimization), PSO (Particle Swarm Optimization), DFA (Dragon Fly Algorithm) and GA (Genetic algorithm) were applied to generate the efficient maintenance feasible routes.

- Performance parameters of each algorithm were depicted in the form of heuristics, execution time and NLFO.

# CHAPTER - 6

# ANALYSIS

## 6.1 Graphical Analysis

Based on the test parameters given in table 5.1 and results obtained (table 5.2) graphical analysis was carried out for all test cases. Graphs depicts the analysis of the heuristics results obtained after implementing each optimization algorithm and the performance of each algorithm with respect to the execution time. All the optimization algorithms were applied on the same processing machine using MATLAB, and their results were recorded. Same are illustrated and discussed below: -

- We can analyse from Case 1-3 that DFA and PSO generated the most optimized results, whereas, GA and MFO produced worst results. However, in case of execution, least time was taken by MFO and then DFA.

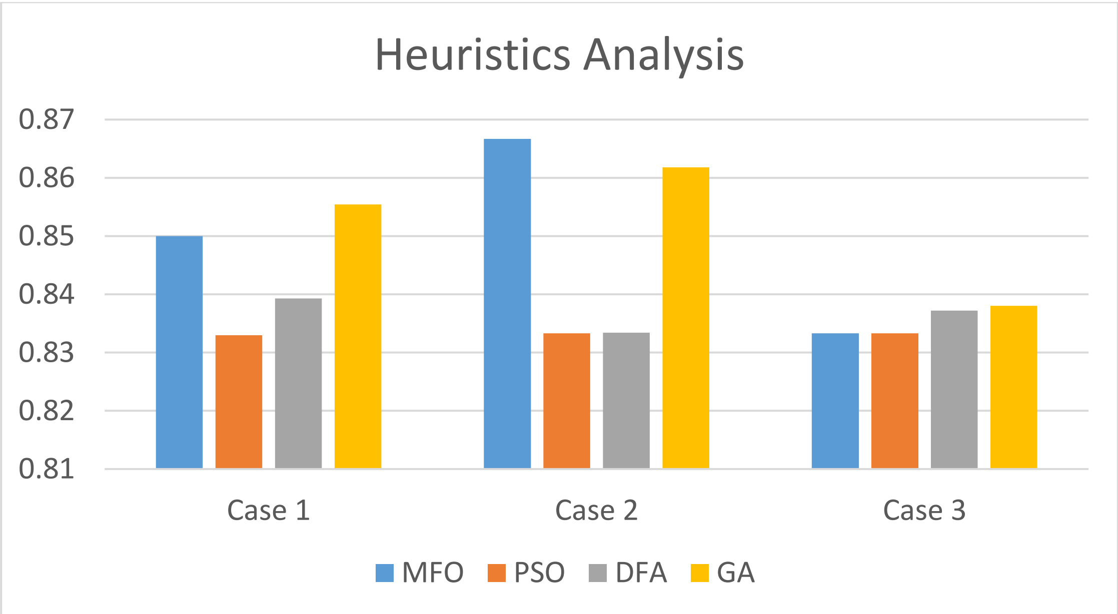


**Figure 6.1** Heuristic analysis of case 1-3

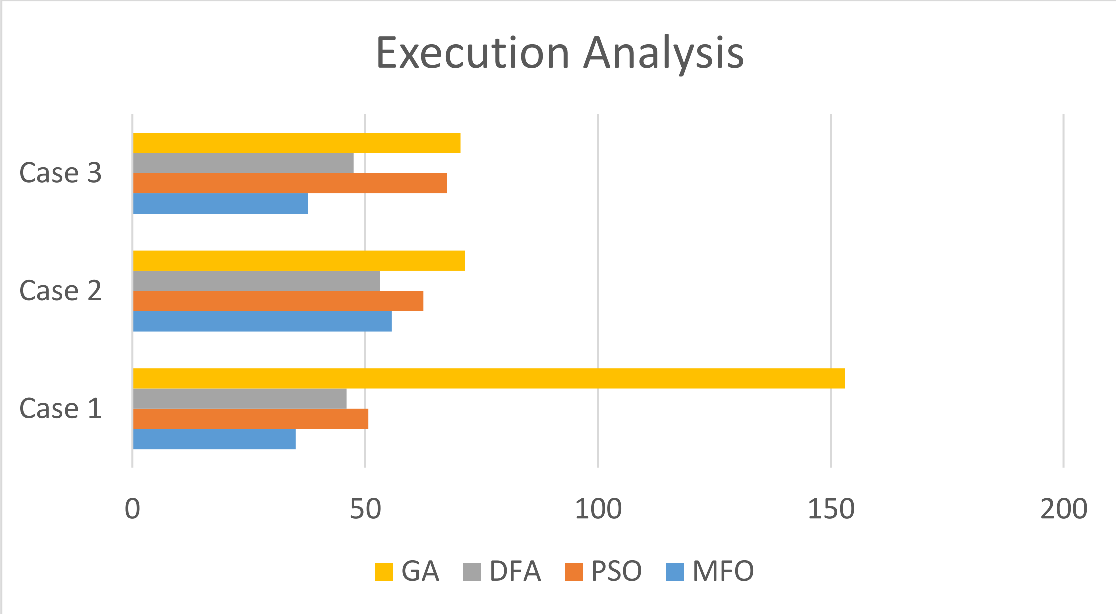


**Figure 6.2** Execution analysis of case 1-3

- Heuristics analysis of case 4 to 6 depicts that best results were obtained by PSO, whereas, MFO produced the worst result. However, least execution time was taken by DFA and worst execution time was taken by PSO and GA.

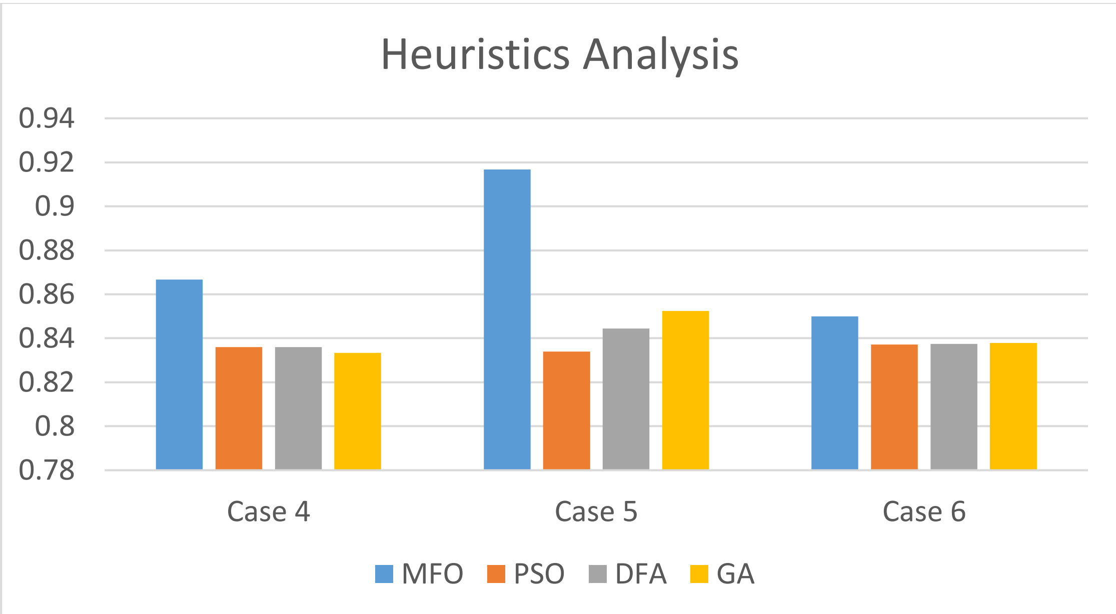


**Figure 6.3** Heuristic analysis of case 4-6

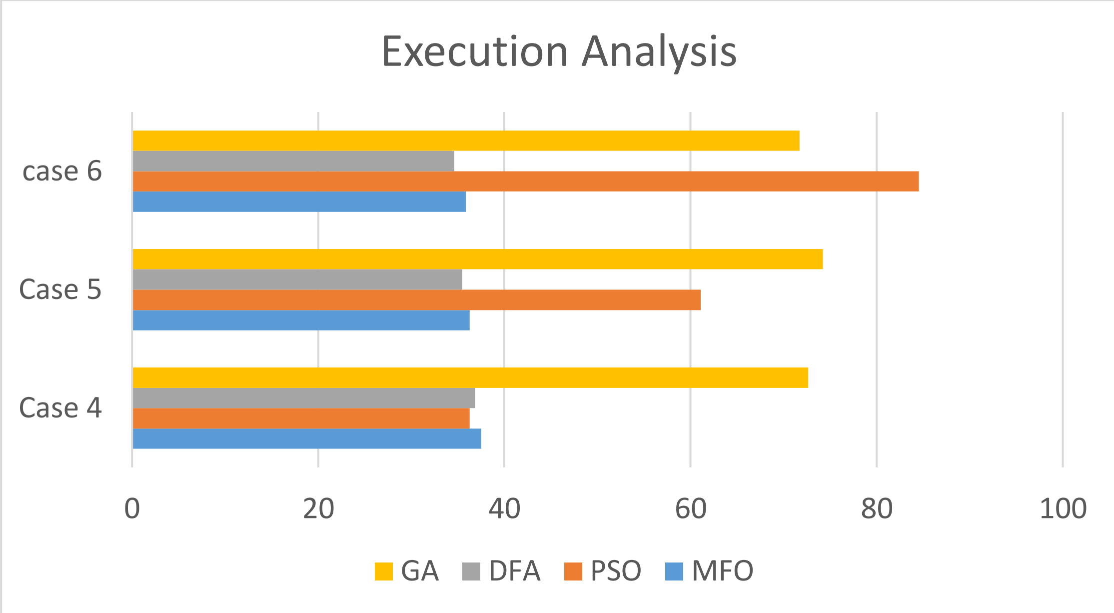


**Figure 6.4** Execution analysis of case 4-6

- Test case 7 to 9 depicts that the heuristics results for each optimization algorithm were same. However, execution results display that least execution time was taken by DFA.

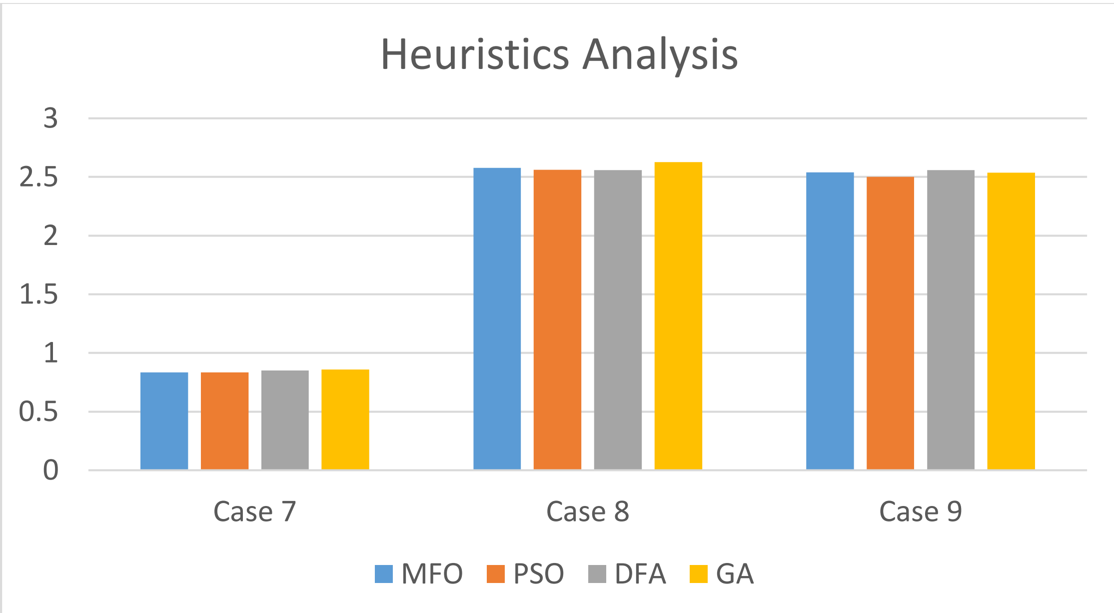


**Figure 6.5** Heuristic analysis of case 7-9

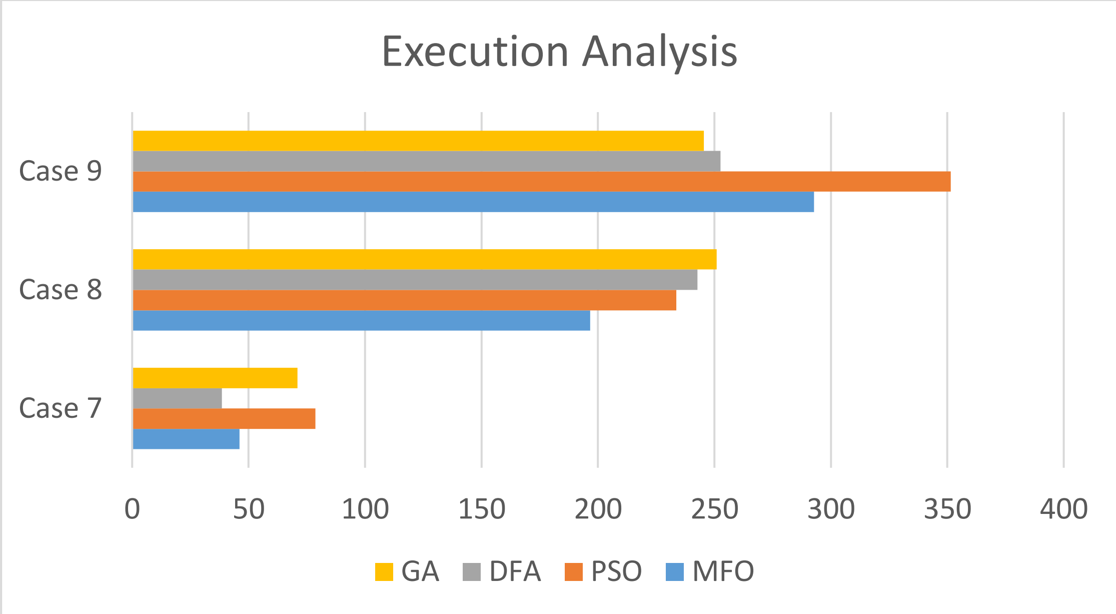


**Figure 6.6** Execution analysis of case 7-9

- Heuristic analysis of test cases 10 to 12 shows that best optimized routes was obtained using MFO and DFA, whereas, lest execution time was taken by MFO in case 10 and 11, where as, DFA took lest time in case 12.

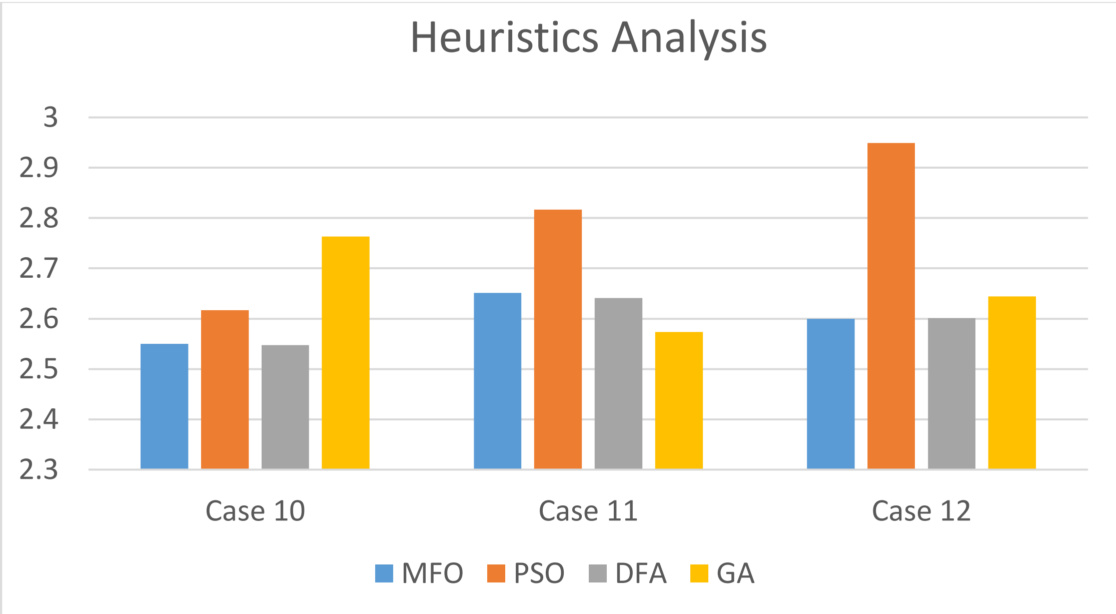


**Figure 6.7** Heuristic analysis of case 10-12

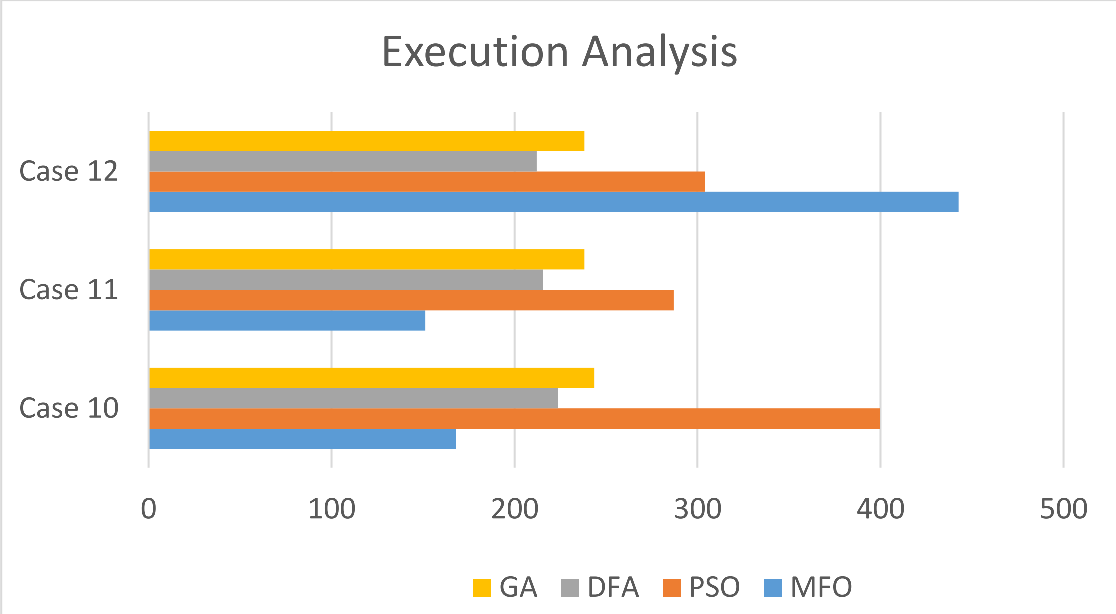


**Figure 6.8** Execution analysis of case 10-12

- Test case 13, 14 and 15 shows that the heuristics results for all four cases is same, however, least execution time was taken by DFA.

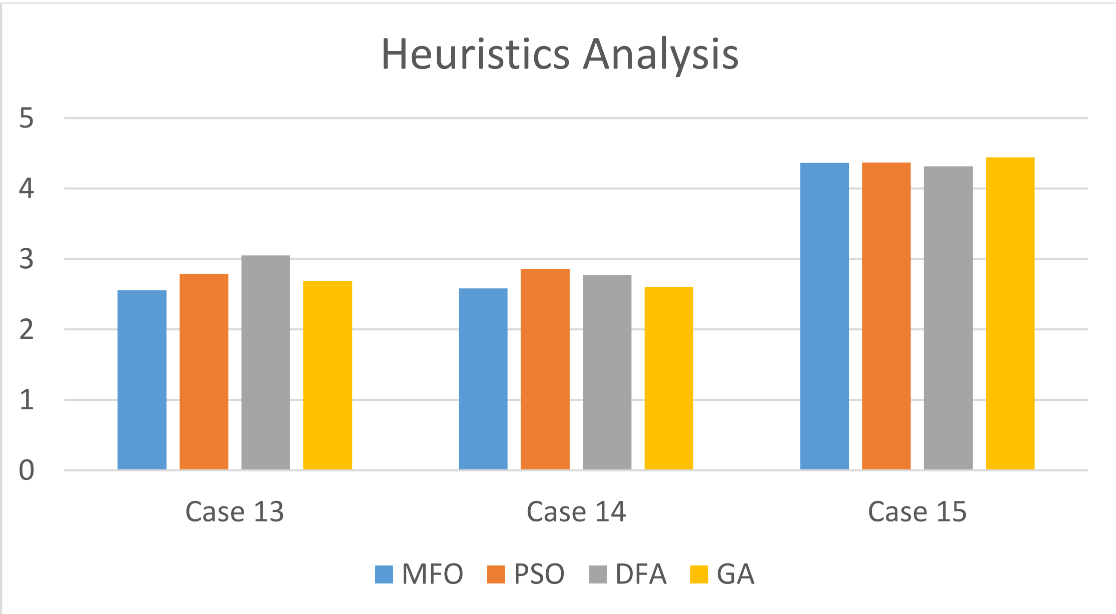


**Figure 6.9** Heuristic analysis of case 13-15

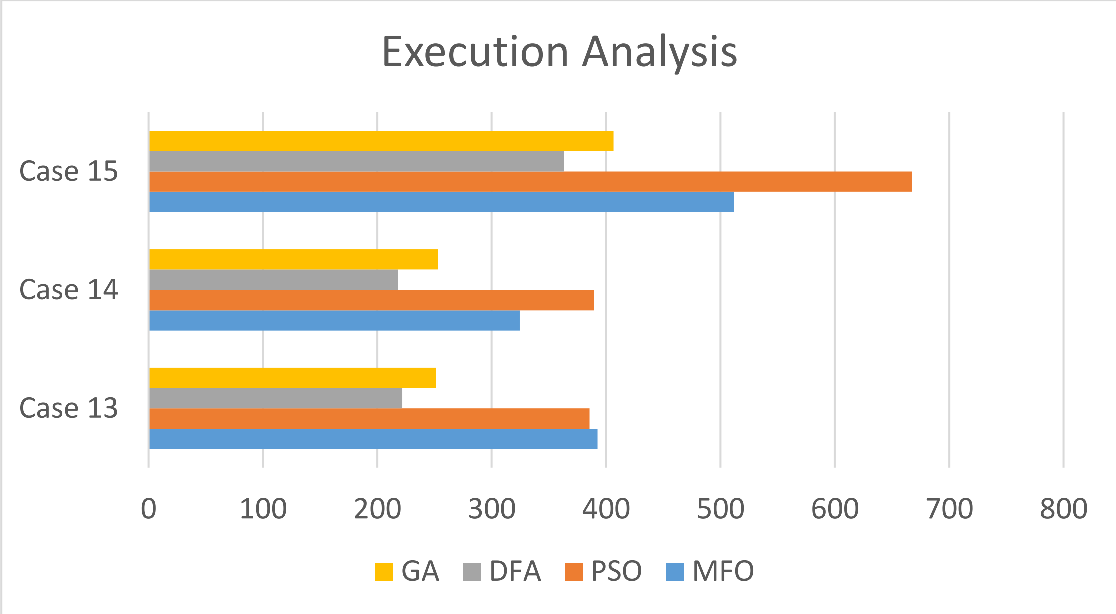


**Figure 6.10** Execution analysis of case 13-15

- Heuristic analysis of test case 16, 17 and 18 depicts that the most optimal routes were generated by MFO for case 17 & 18, for case 16 DFA generated the optimal route. Least execution time was taken by DFA in these three cases.

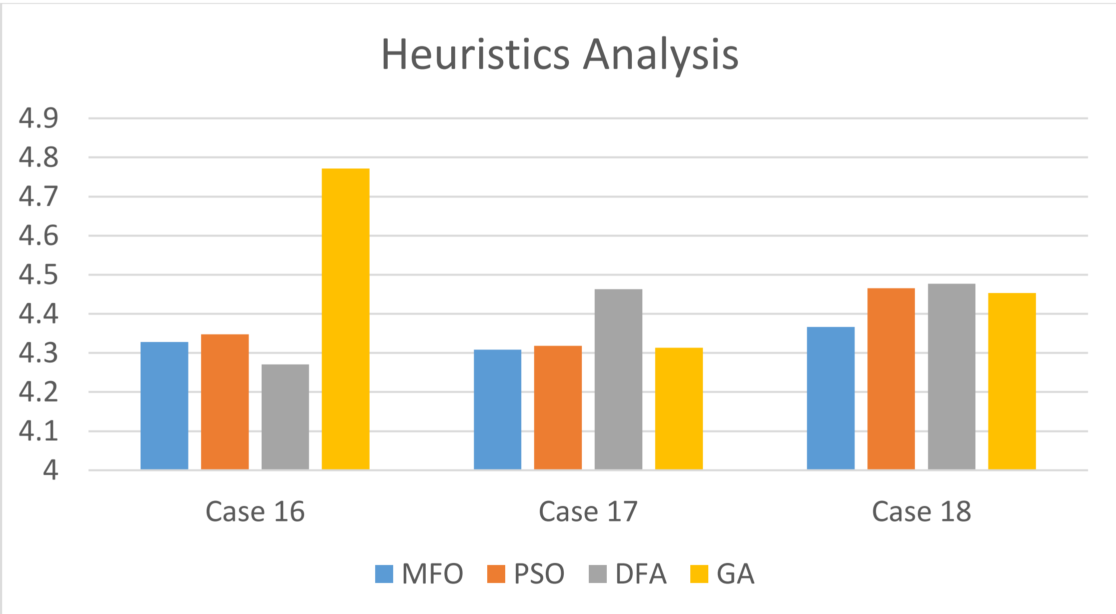


**Figure 6.11** Heuristic analysis of case 16-18

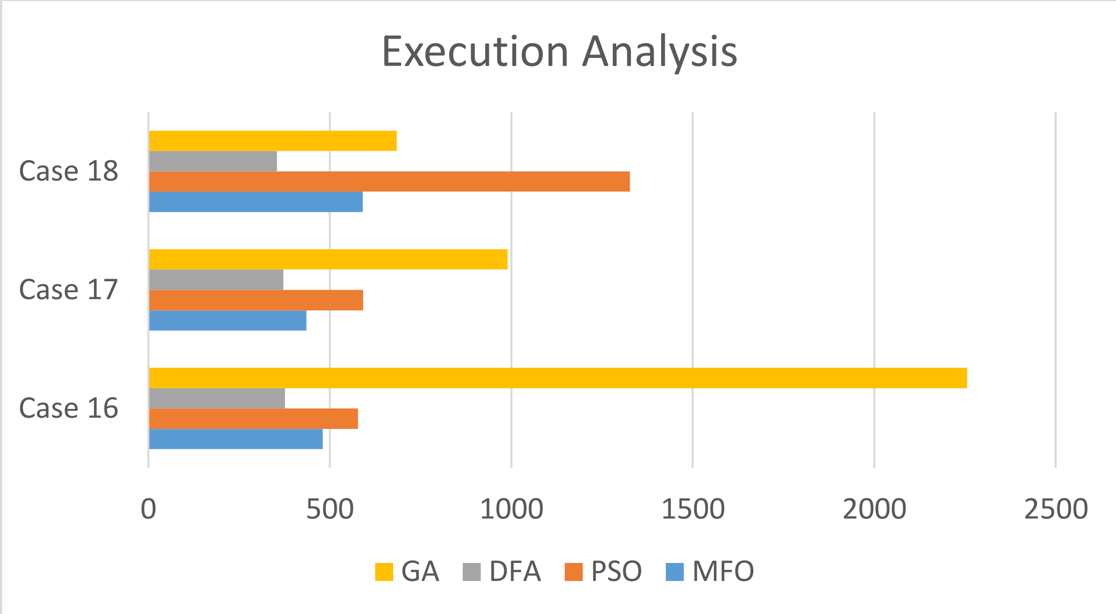


**Figure 6.12** Execution analysis of case 16-18

- Test case 19, 20 and 21 shows that the most optimal routes were generated by MFO and least execution time was taken by DFA.

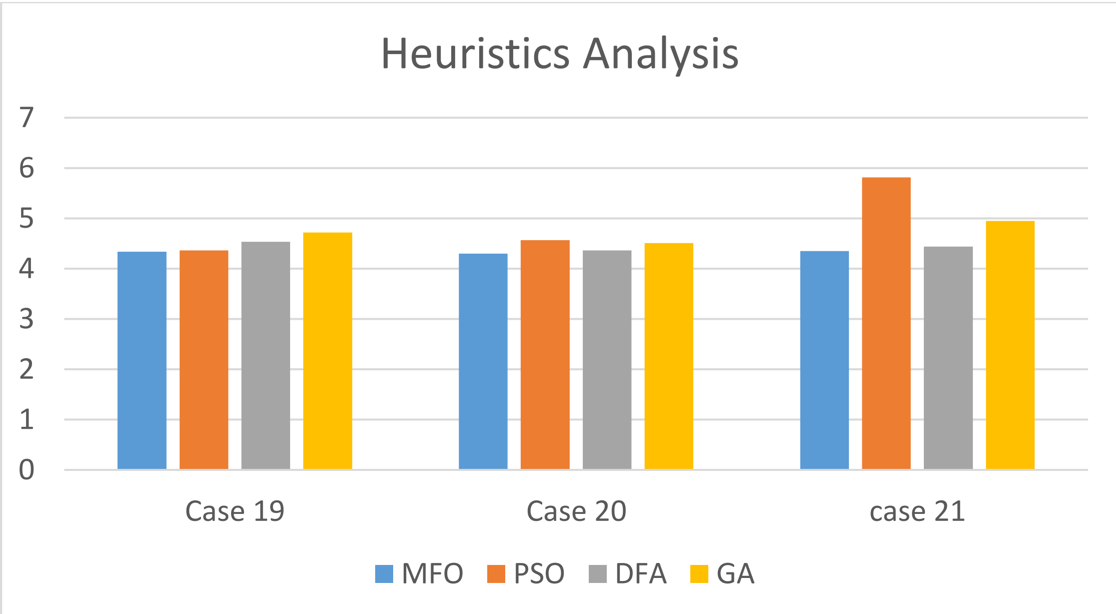


**Figure 6.13** Heuristic analysis of case 19-21

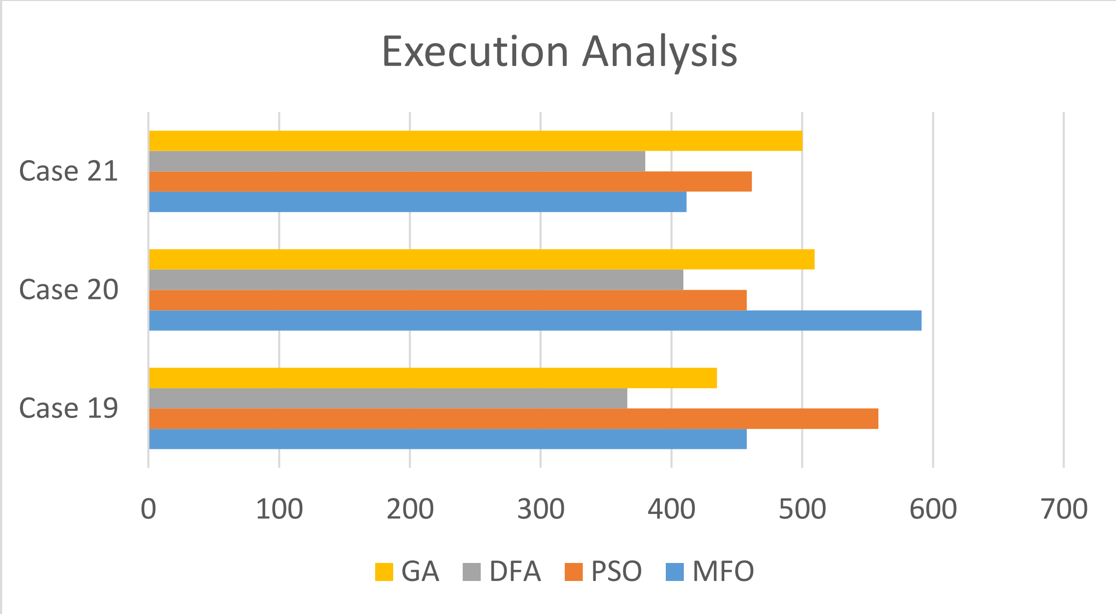


**Figure 6.14** Execution analysis of case 19-21

- Execution time of test case 22, 23 and 24 shows that DFA took the lest time for execution whereas, MFO produced the most optimal results.

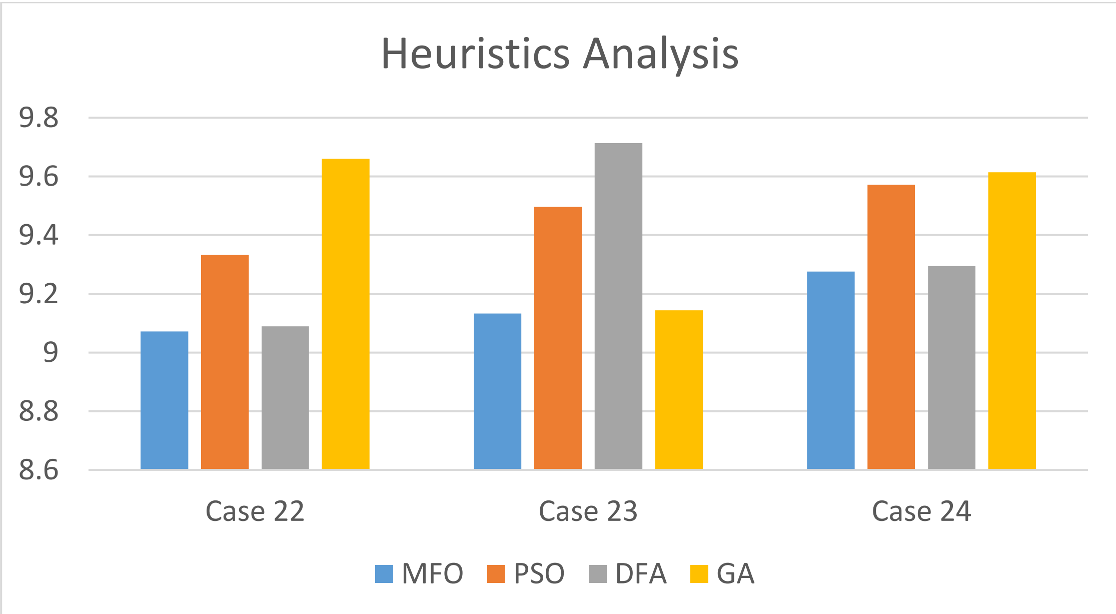


**Figure 6.15** Heuristic analysis of case 22-24

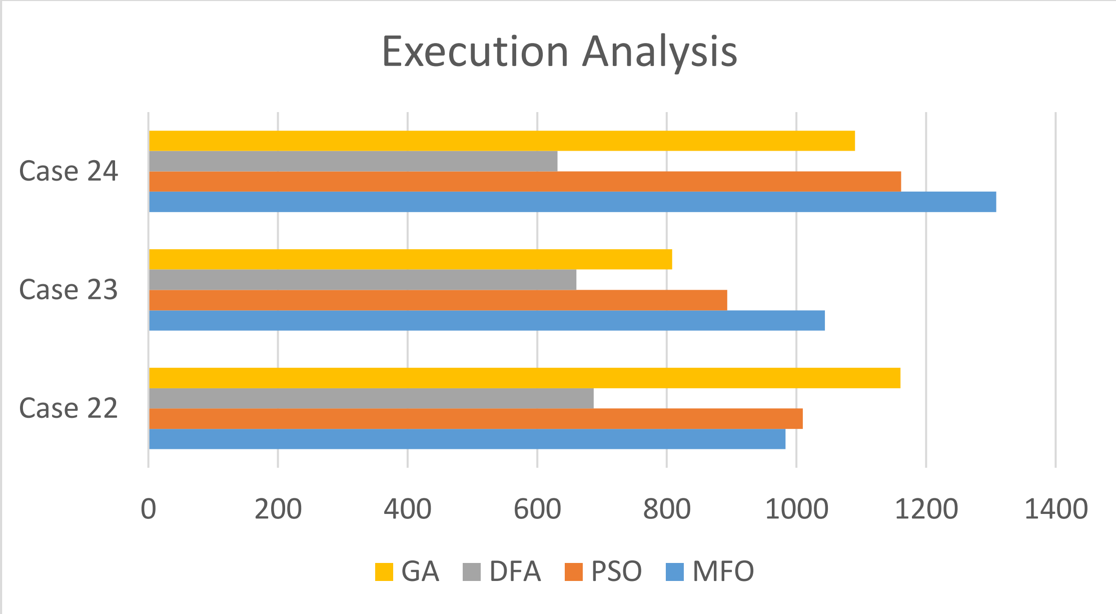


**Figure 6.16** Execution analysis of case 22-24

- Heuristic results of test cases 25, 26 and 27 depicts that the most optimal route was generated by MFO and least execution time was taken by DFA.

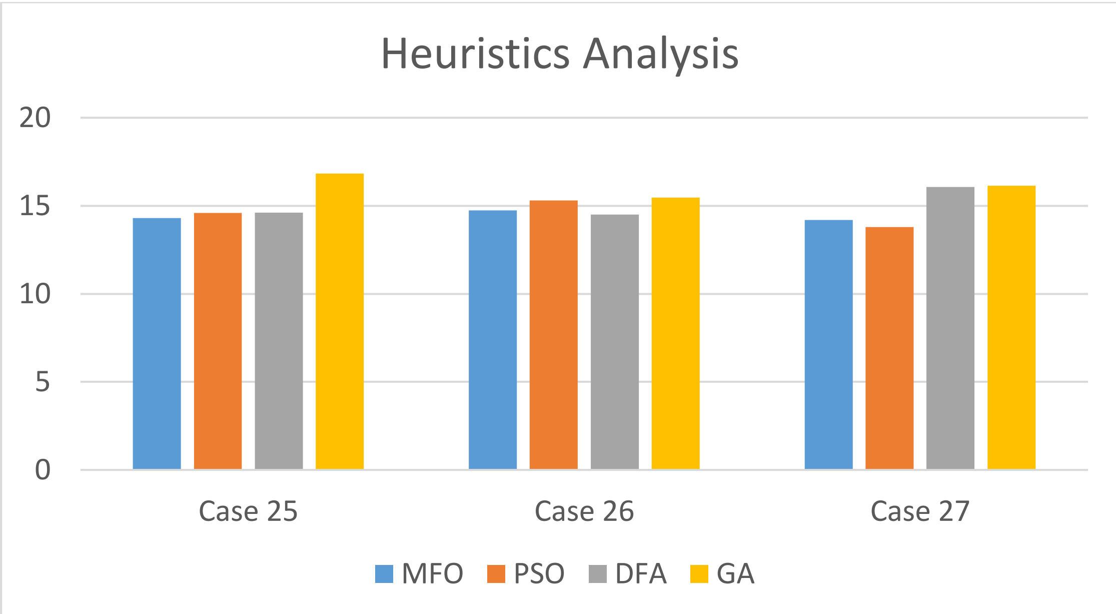


**Figure 6.17** Heurisitc analysis of case 25-27

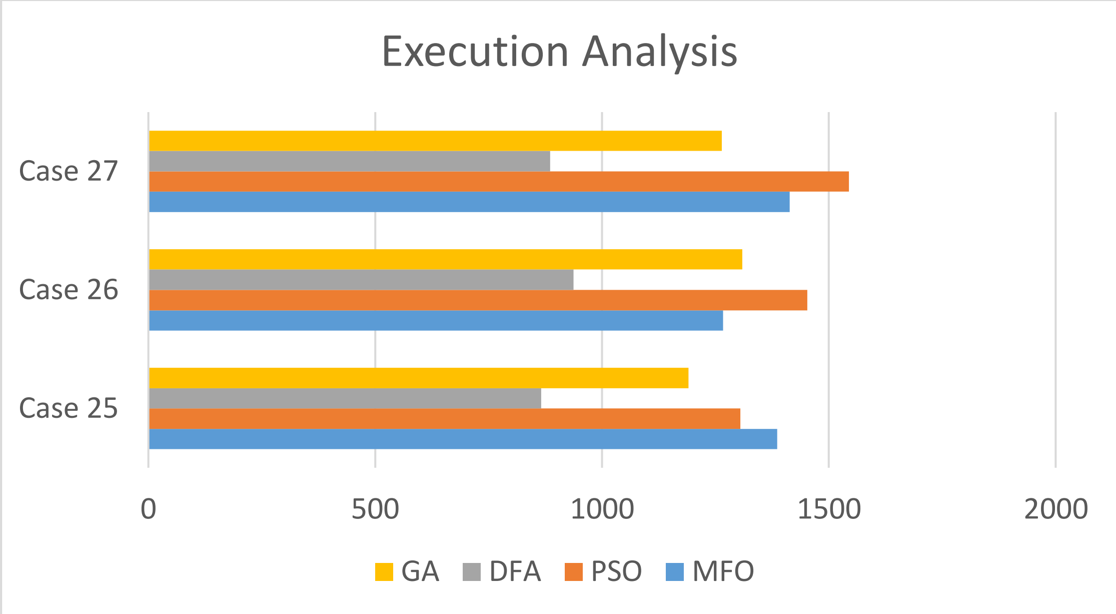


**Figure 6.18** Execution analysis of case 25-27

- Analysis of case 28, 29 and 30 depicts that most optimal routes were generated by the MFO and the least execution time was taken by DFA and worst execution time was taken by MFO in case 28 and GA in case 29 and 30

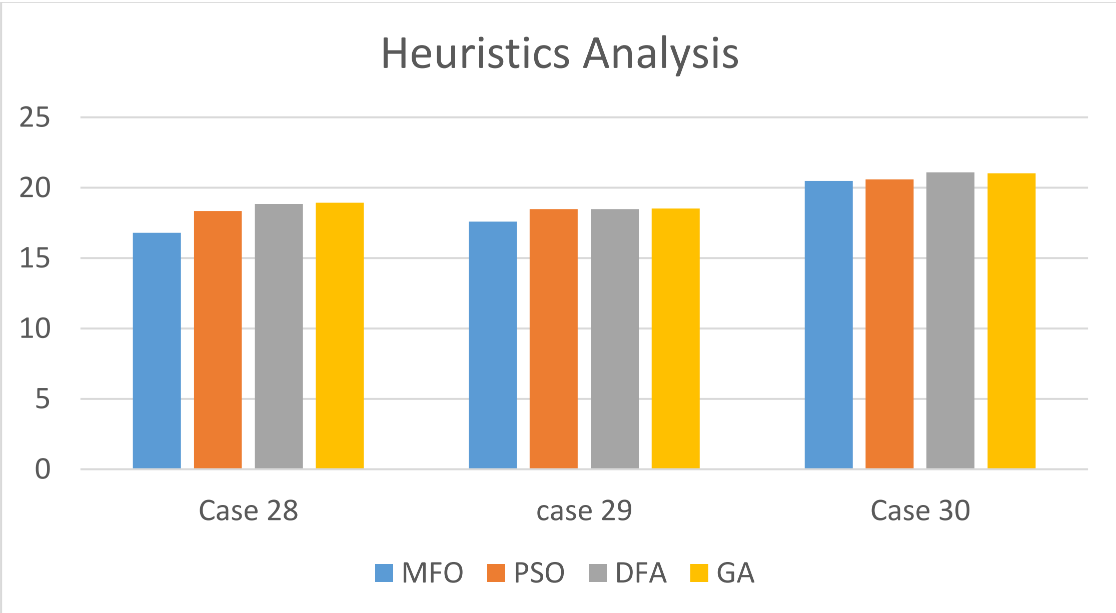


**Figure 6.19** Heuristics analysis of case 28-30

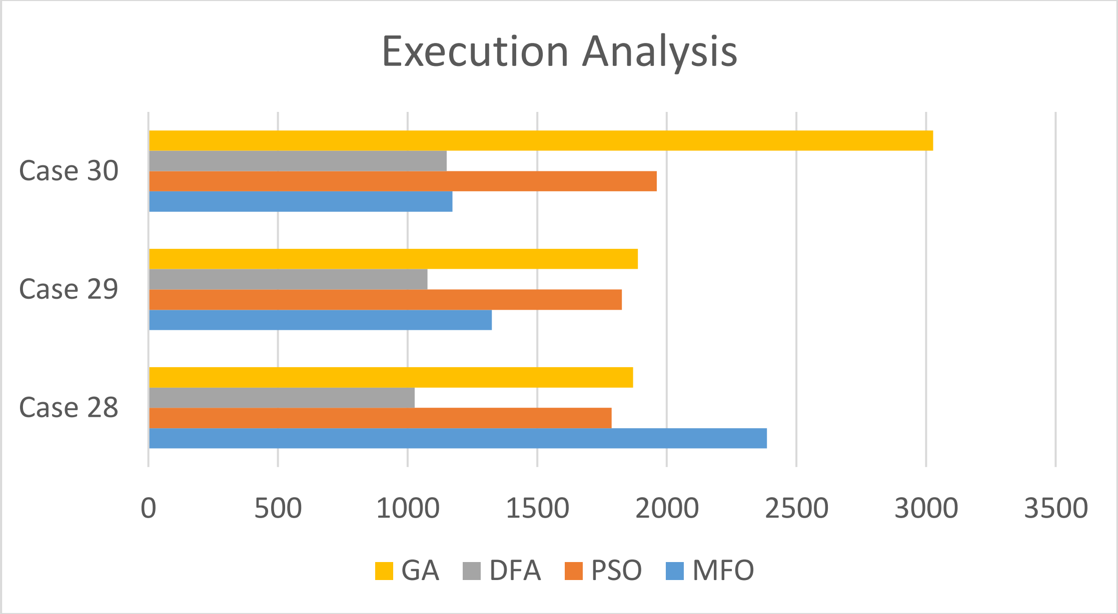


**Figure 6.20** Execution analysis of case 28-30

- Heuristic analysis of case 31 and 32 depicts that the best optimal route was generated by MFO and the worst optimal route was generated by GA, whereas, least execution time was taken by DFA and worst performance was delivered by GA.

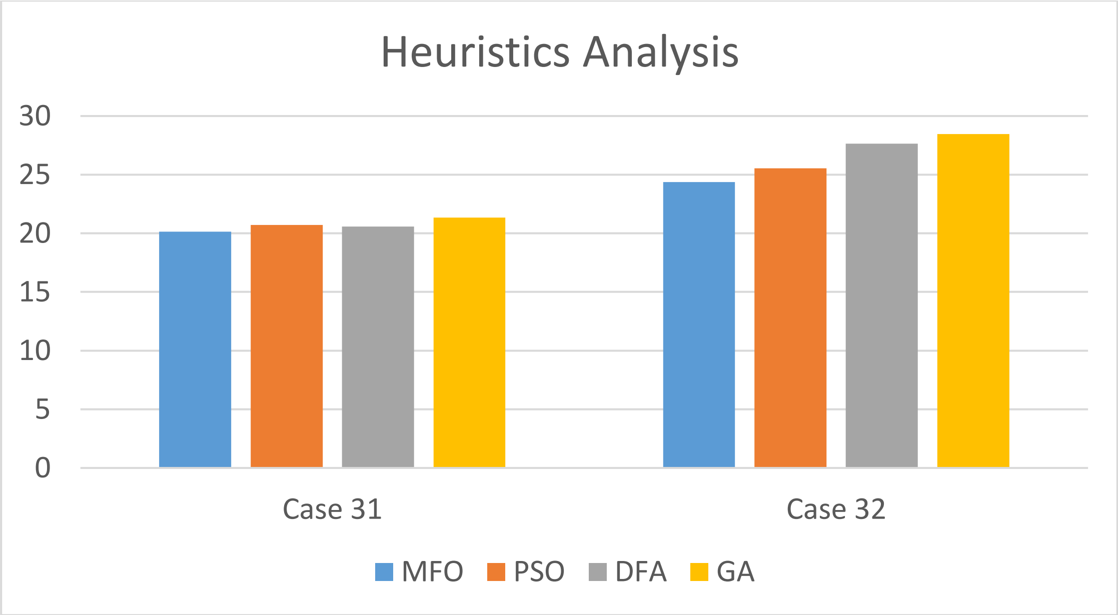


**Figure 6.21** Heuristics analysis of case 31& 32

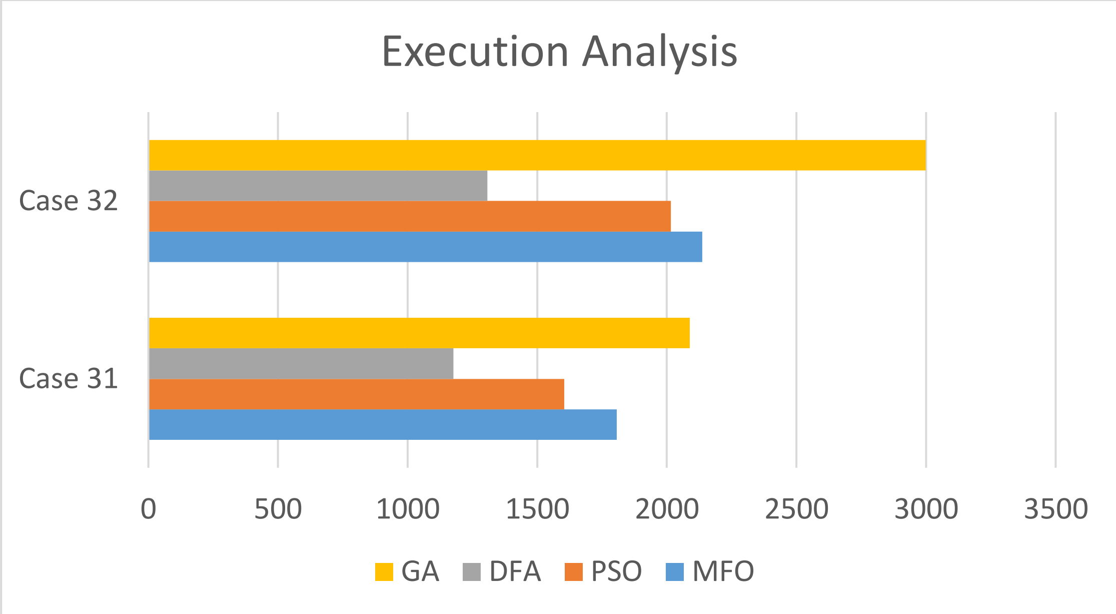


**Figure 6.22** Execution analysis of case 31 & 32

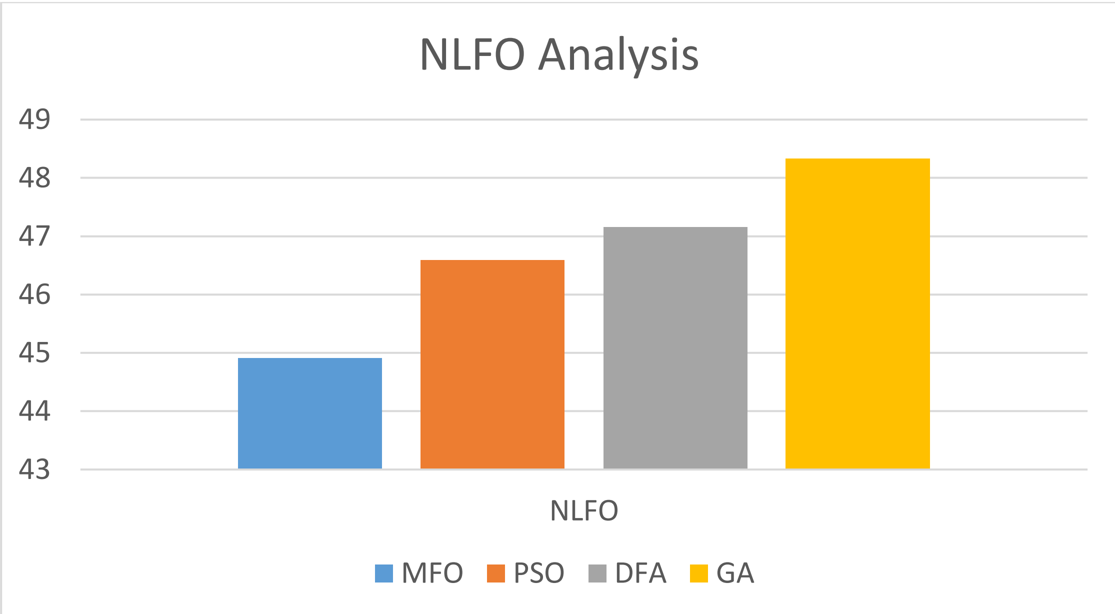


**Figure 6.23** NLFO analysis of all four optimization algorithms

## 6.2 Summary

Overall analysis for number of lost flight opportunities (figure 6.23) shows that the best performance was generated by Moth Flame Optimization Algorithm (MFO), whereas, the worst performance was given by Genetic Algorithm (GA). Keeping in view all the test cases and results obtained, it is evident that for the route optimization for a small network airline, PSO produces the best results with respect to heuristics, however, in case of complex scenarios, where there are more than 61533 flights, 743 origin destination pairs, 150 cities and 25 aircrafts, Moth Flame optimization produces better results in terms of heuristics. However, in terms for execution time the best results were given by Dragon Fly Algorithm.

# CHAPTER – 7

# CONCLUSION AND FUTURE WORK

## 7.1 Conclusion

The proposed work presents a novel approach for generating the optimized maintenance feasible route for an aircraft which is due for maintenance. **"Aircraft maintenance routing"** being one of the challenging and important aspect for an airline is critical for efficient operations. An efficiently planned route always ensures the maintenance aspect and serviceability for an aircraft while taking into consideration all the additional parameters related to maintenance like the availability of maintenance station, availability of man hours. This research was aimed on reducing the overall cost incurred during re-assignment of aircraft to a flight leg meanwhile reducing the cost incurred due to illegal assignment of maintenance station. Based on the objectives discussed initially we have successfully devised a novel technique for route generation using **"Breadth First Search"** and **"Dijkstra's algorithm"**. For optimized route generation, we have used four different types of algorithms namely MFO, PSO, DFA and GA. After analysing the results, it can be concluded that MFO (Moth Flame Optimization Algorithm) is the best optimization algorithm in the cases of complex and huge flight networks, whereas, in case of execution efficiency DFA (Dragon Fly Algorithm) produces better results even in complex scenarios.

## 7.2 Future Work

Future work involves further integration of aircraft crew pairing & scheduling with the current aircraft maintenance scheduling to further reduce the cost of crew assigned for an individual aircraft, which is due for maintenance. Furthermore, other optimization techniques like predator prey and Ant Colony Optimization may also be investigated to get more optimized and efficient paths.

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