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FLIGHT PLAN ROUTE OPTIMIZATION AND INCREASE THE PROFIT IN AIRLINE INDUSTRY BY USING HYBRID BCF ALGORITHM

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Abstract

Airline industry is a booming industry where decisions have to be taken in the dynamic environment. There are many factors which govern the decision-making namely the airline route as considerate amount of profit can be generated by selecting the optimized airline route. The paper proposes a hybrid BCF algorithm which optimizes the flight trajectory and seat allotments. The algorithm specifically optimizes the airline route, seat allotment on a large scale of data set to give the best option to choose in and implement it. The result shows the tremendous variation regarding the net amount there by increasing the profit.

Keywords:

Hybrid BCF Algorithm, Decision-Making, Optimized, Airline Route, Profit

1. INTRODUCTION

The airline will be able to optimize its profit in several sectors both in the short and long term. Airlines that are categorized in long-term decisions are most importantly allocated to their fleet. The decision depends on various factors available, the benefit of every possible flight, popularity in the region, specific airport restrictions, crew scheduling and so on. Crew planning also constitutes a long-term optimization criterion, which assigns the staff to each flight so as to minimize the operating costs of the flight. There are many restrictions in the assignment of the fleet, crew planning and solving such problems is made more complicated [7]. The work shift and regulations, employee preferences, landing on the same location and more are some of the constraints. If you plan the flights, you have to optimize the routes. It becomes very difficult because before few hours of flight departure the route schedule has to be carried out. The weight of the aircraft (including passengers and freighters) and the weather data and prices for the fuel are the information required to plan the route. Worldwide airspaces are divided into route point’s networks.

The airlines plan a route to their destination airport from their departure airport. The route is forwarded to the Air Traffic Control responsible for monitoring all struggles in the region. It is a traditional shortest way problem to achieve this, where the monetary costs must be reduced to a minimum. Regional air traffic charges, track dependencies and other constraints are however complicated [9]. The restrictions are quite diverse and are revised every few hours in order to take account of current air traffic flows in the particular flying region [8]. Route projection is a key component of good network planning. The route must be optimized in order to generate the total cost over the revenue. Therefore, it is necessary to choose the optimum route for a flight that influences its costs significantly. A route describes the path an aircraft travels between airports. Most commercial flights will be operated from one airport to another but the same airport that they departed can take private planes, commercial sightseeing tours and a military aircraft on or off the airport.

2. OPTIMIZATION OF THE FLIGHT PLAN

An operational flight plan is required to ensure the aircraft complies with all of the operational requirements on a specific flight; to provide the crew with the information needed to help them to conduct the flight in a safe manner and to coordinate with the Air Traffic Control (ATCs) [23] [25]. The selection of a more efficient system and all its analytical and optimization functions offer advantages. Flight planning not only saves money but also helps the environment: CO_2 emissions are directly commensurate with the burning of fuel, with CO_2 emitting at more than 20 pounds. A plan for flights includes the flight route and specifies altitudes and velocities. It also calculates the volume of fuel used by the aircraft and the additional fuel needed to comply with several safety requirements. An effective flight scheme can reduce fuel costs, time based costs, overflight costs, and loss of payload income that cannot be carried, by altering the route (e.g. ground tracks), altitudes, speeds and amount of departure fuel. These changes are subject to aircraft performance, the weather, road and altitude structures permitted, schedule restrictions and operating restrictions. Although safety and regulatory compliance require flight plan calculations, these also provide airlines with the possibility to optimize cost by determine the optimal aircraft route, altitude, speed, and load fuel volume [21] [22].

Optimization can be difficult because a number of different elements are involved. Not only should the correct physics (i.e. aircraft performance and weather), but also the ATC route restrictions and all relevant regulatory restrictions be taken into account in an optimized flight plan. The mathematical nature of these limitations and the overall size of the calculation make it even with modern optimization standards a challenge. Some of the behavioral equations are nonlinear and non-continuous, and the state of the airplane is dynamic (i.e. depends on how the airplane reaches a certain point not only where it is). Consequently, a single flight requires tens to hundreds of thousands of individual calculations.

An optimal flight plan scenario for save fuel and emissions requires multiple routes or operating approaches for each airplane to be calculated, these scenarios to be ranked by total cost, the scenario to achieve its best cost objective will be selected, and other operational flexibility scenarios will be summarized. Dispatcher and operations manager of a control center of an airline can choose an additional scenario to fulfill its operational objectives, such as routing aircraft, crews and passengers, although the system can use most of the time. Since these choices are often made soon before departure time, it is vital that the relevant information be presented user-friendly.

3. ROUTE OPTIMIZATION

The best way of flying depends on the current flight conditions. These include the projections of high air winds and temperatures, payload amounts and timeshares that day [16] [22]. These include: The time costs for the crew and the airplane are particularly vibrant due to the value of the payload and the schedule and operating constraints. Winds can have a major impact on the optimal route: they can be very far from the large circle route. The National Weather Service (NWS) and Meteorological Office (MEO), each updated one to six hours, are used for winds in all calculations of the flight plan [26] [27].

Already, although nearly all computer flight scheduling systems can optimize routes, most of the time many airlines still use fixed routes [19]. The fact that ATC organizations, over flight permits and company policies limit the routing of certain areas has been limited to one reason for adopting dynamic route optimisation [24]. The efficient flight plan system includes models of all these restrictions that are then used in numerical optimization [6] [10] [11] as restrictions. This enabled a flight plan to be optimized, while still complying with all constraints, by dynamic wind, temperature and cost data. This paper offers a hybrid heuristic approach in which the route is optimized and seat allocation is optimized with priorities.

4. PROPOSED OPTIMIZATION ALGORITHM

The use of metaheuristic algorithms has exceeded the horizon in recent years [18]. By using it in the assessment of the data set, it makes the optimization of the data set much possible according to the requirements. In order to increase net profit, the proposed algorithm aims at optimizing the flight path with dynamic sitting allocation [14] [15] [17].

The proposed algorithm is a decision support solution that helps airlines assess a certain schedule's networking profitability in order to contribute to strategic and long-term planning.

The route profitability is improved with the cumulative proposals of Meta-heuristic algorithms, such as the Firefly algorithm (FA), the BA-algorithm (BA) and the BCF hybrid (CSA) [1]-[4].

Using PL/SQL, dynamic programming (DP) is used to identify expected costs for each route, path, seat, freight, or mail. The main update formula for any pair of two flights on different source airports is x_i and x_j is:

$$a_i^{t+1} = a_i^t + \beta \exp\left[-\gamma r_{ij}^2\right]\left(a_j^t - a_i^t\right) + \alpha_t \varepsilon_t \tag{1}$$

The objective is to reduce or maximize the total anticipated airline route expenditures [28]. The fitness value of the company and the route is calculated using DP. The suggested model uses three algorithms to generate the first particles to deal with the airliners, using Nearest Neighbor Heuristic (NNH). The algorithm is used by SQL and the number of air traffic data established between Jan 2009 and November 2014 differentiates. It produces very competitive and time-consuming results [29].

Pseudo code for hybrid BCF algorithm for route profitability based on passengers, freights and mails:

Step 1: Begin

Step 2: Define objective function for flights: $f(a)$, $a = (a_1, a_2,\ldots,a_n)$;

Step 3: Generate an initial population of flights $a_i = (a_1, a_2,\ldots,a_n)$;

Step 4: Generate an initial population of destination ports $b_i = (b_1, b_2,\ldots,b_n)$;

/*******Adopting Bat Behavior Here*********/**

Step 5: Map the airliners to the ports destination (including halts) $c_i = ((a_1b_1), (a_1b_2),\ldots,(a_nb_n)$ as a $m\times n$ matrix format

Step 6: Compute pulse frequency f_i for all matrix records with respect to available flights and their distance $A_i = x_iy_i$ where A_i is the loudness (to resemble the Bat Sonar response time)

Step 7: Compute pulse rates for each port for a given point of time r_i (To find the number of hits on destination port)

/*******Adopting Firefly behavior*********/**

Step 8: Based on overall results from Step, group the airliners and the ports by f_i and A_i (Since the fireflies club together where there is a (atmost) equal frequencies of flasing light)

Step 9: Name Each group as G_i

Step 10: Define absorption coefficient$_\gamma$(average allocations, available parameters cannot be filled at once)

/*Computing parameters for generated fitness value***/**

Step 11: Formulate the seat/freight/mail availability of light intensity (I) so that it is associated with flights $f(a)$

Step 12: For maximization problems, $I\alpha f(a)$(availability based on individual airliners) or

Step 13: $I=f(a)$ (mark the availability for each airliner)

/*******Adopting the Cuckoo behavior*********/**

Step 14: While (number of airliners n<MaxGeneration G_i (available destination ports X available source ports)) /* From Firefly results after grouping based on frequency computed on Bat method*/

Step 15: for $i = 1{:}n$ (all n flights)

Step 16: for $j = 1{:}n$ (n flights)

Step 17: if $(I_i > I_j)$, /* Firefly allocation */

Step 18: If the same airliner with same destination on the other port has more availability, then,

Step 19: Move flight i towards j;

Step 20: If$(\text{rand} < A_i \& f(x_i) < f(x_n))$ /* Ranking method on Bat */

Step 21: Accept the new solutions

Step 22: Increase r and reduce A_i

Step 23: (move flight params from a to b and carry out allotment then fly to destination c) /* Cuckoo behavior of moving original host to the next available feasible host) */

Step 24: end if ; /* Ranking adopted from Bat behavior */

Step 25: end if ; /* End of Firefly allocation */

Step 26: Vary (attractiveness) fitness with route (distance between source and destination) r via $\exp(-\gamma r)$;

Step 27: Evaluate new solutions and update new availability(light intensity);

Step 28: Compute profits.

Step 29: end for *j*

Step 30: end for *i*

Step 31: Display the computed profits and other allocation parameters after matching.

The SQL implements the proposed hybrid BCF algorithm for route profitability analysis using data from the Australian aviation data [12] [13]. The data set included 124 records of 53 Australian ports and 57 foreign ports consisting of 30000 separate airport records between January 2009 and November 2014 [5], respectively.

Table.1. Hybrid BCF algorithm Results

Parameters	Hybrid BCF algorithm	Actual Data
Month	14-Nov	14-Nov
Year	2014	2014
#Airliners	27	27
#Australian ports	9	9
#Countries	32	32
#Foreign ports	55	55
Total distance	765696	765696
Total Pax capacity	995113	995113
Total Pax in	865678	865678
Total Freight capacity	42400	42400
Total Freight in	22557.4	22557.4
Total mail capacity	12400	12400
Total mails	1638.2	1638.2
Total Fuel capacity	1301683.2	1301683.2
Total Fuel used	1225113.6	1225113.6
Total Income	30200675073	29900812861
Total Expenses	27058044202	27225855965
Total Profit	3264923343	2860481165
Total loss	122292472	185524268.9
Nett	3142630871	2674956896

The proposed algorithm gives us the most optimal flight path that is indeed the flight route between several airliners in coordination with passenger allowance based on constraints such as departure time and availability. The allocation of passengers is only possible with airliners/routes. Functions depends on distance of route, passenger/freight/mail capacity. Not all ports/airliners and destination ports/airlines are taken into account [9].

Due to availability of the seat and requirement of passengers as departure periods, passengers are shifted to their home and other airline companies to make the aircraft possible use. Small aircraft may allocate the others to reduce the operating costs for the flight. Seats, cargoes and mails for several airlines will be allocated. In terms of profit, loss and net amount, the Bat Algorithm has exceeded the Bat algorithm. In Fig.3, the contours are the same. Fuel, income, expenses, profit, losing as well as the net amount shown in Table.2 (Fig.1) and Table.3 (Fig.2), where the main optimized parameters are given in Table.1.

Table.2. Hybrid BCF algorithm

Parameters	Actual Data	Hybrid BCF Algorithm
Total Income	3	3.1
Total Expenses	2.8	2.7
Total Profit	2.8	3.4
Total Loss	1.8	1.3
Net	2.6	3.2

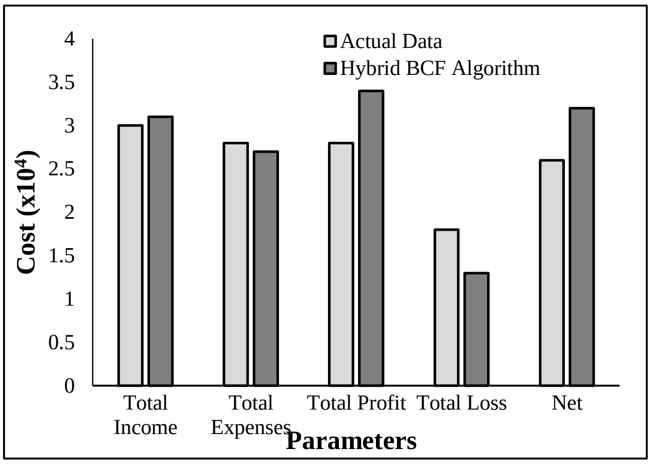

Fig.1. Hybrid BCF algorithm

Table.3. Parameters variations

Parameters	Actual Data	Hybrid BCF Algorithm
Total Income	2.8	2.9
Total Expenses	2.4	2.4
Total Profit	0.3	0.4
Total Loss	0.1	0
Net	0.2	0.4

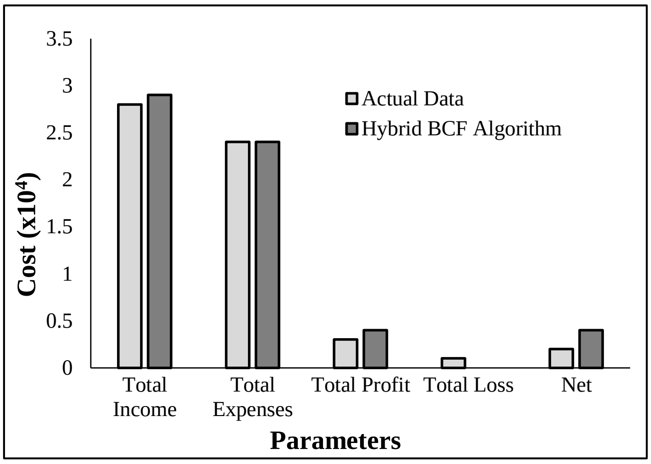

Fig.2. Parameters variations

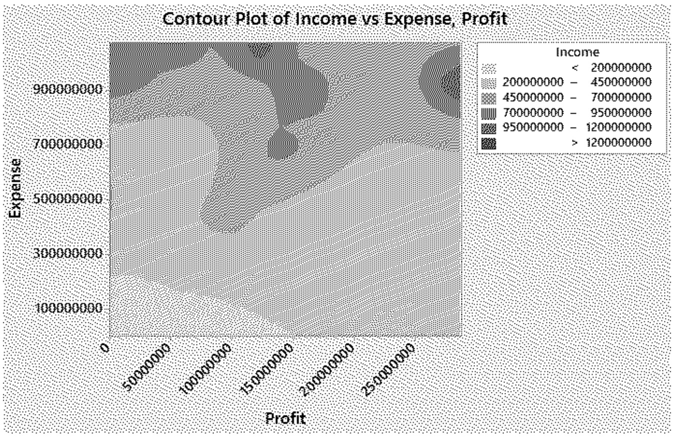

Fig.3. Income vs. Expense Profit

5. CONCLUSIONS

Accurate, optimized flight plans can save airlines millions of gallons of fuel every year without forcing the airlines to compromise their schedules or service. Airlines can realize their benefits by investing in a higher-end flight planning system with advanced optimization capabilities and then ensuring accuracy by comparing flight plan values to actual flight data, identifying the cause of discrepancies, and using this information to update the parameters used in the flight plan calculation. Current research in flight planning system development ensures that flight planning systems take full advantage of airspace and air traffic management liberalization and work together with other airline operations systems to produce the best overall solutions. The proposed algorithm pays off more in terms of net amount which indicates the profit and it has shown 12.5% improvement over the bat algorithm which is the benchmark. The future work may focus on the traffic forecasting and airport capacity restriction which are some of the vital parameters in which the airline industry should throw light

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