Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 87 (2016) 86 – 92

Procedia Computer Science

Fourth International Conference on Recent Trends in Computer Science & Engineering.

Chennai, Tamil Nadu, India

Airline Route profitability analysis and Optimization using BIG DATA analyticson aviation data sets under heuristic techniques

Kasturi E[a]*, Prasanna Devi S[b], Vinu Kiran S[b], Manivannan S[c]

[a]*Phd Scholar, MS University, SSE, Saveetha University, Chennai 600072, India*
[b]*Department of Computer Science & Engineering, Apollo Engineering College, Chennai 602105, India*
[c]*Deputy Dean, Dr.MGR Educational & Research Institute University, Chennai 600107, India*

Abstract

Applying vital decisions for new airline routes and aircraft utilization are important factors for airline decision-making. For data driven analysis key points such as airliners route distance, availability on seats/freight/mails and fuel are considered. The airline route profitability optimization model is proposed based on performing Big data analytics over large scale aviation data under multiple heuristic methods, based on which practical problemsareanalysed.Analysis should be done based on key criteria, identified by operational needs and load revenues from operational systems e.g. passenger, cargo, freights, airport, country, aircraft, seat class etc.,The result shows that the analysis is simple and convenient with concrete decision.

1. Introduction

Airline industry is a very large and growing industry throughout the world. Even the discrimination of developed country and developing country does not count for it. International Air Transport Association the IATA forecasts that the international air travel will grow by 6.6% per year on an average till the end of the decade. The fast growing industry provides a vital role in expanding,exploration the economy widely. The airline industry exists in an intensely competitive market. In our study we have analysed that the fuel cost can be controlled which is a major factor which is deterministic in nature. Whereas the other factors like weather labour cost are undeterminstic due to many interdepended parameters.A number of factors are forcing airlines to become more efficient in terms of cost, comfortability, distanceproximity, time and many more.

Big Data - represents a very large volume of data that exponentially grows and ensures availability of both structured and unstructured nature. Big data is high volume, high velocity with a high variety information that requires new methods or forms of processing to enable enhanced decision making, insight discovery and process optimization. 3Vs model is frequently referred for describing big data[2,3].

Volume- Airline and aircraft data growth have always been growing exponentially, from a single byte of data it has grown into peta bytes of data generated every hour with addition of different data sources like engine, route, passenger, bookings etc., Big data on airline industry differs from other conventional methods by its virtue of storing large sets of data.

Velocity- Very large amount of flight data is generated and there an essential need that to be analyzed in real time, where the comparison is performed between the past data to predict the outcome based on the

* Corresponding author. Tel: +0-984-192-0378
E-mail address: kasthoori.e@gmail.com

Peer-review under responsibility of the Organizing Committee of ICRTCSE 2016
doi:10.1016/j.procs.2016.05.131

airline and their route functionality. Big data on airline route requires processing large varieties of data within seconds which makes themdiffer from other technologies.

Variety - Data type of generated airline data is not uniform. It differs from the original data set. Some data types of aircraft parameter may be structured some may not (such as route map will be image form etc.,) Several big data technologies are capable of even handling huge varieties of this type of data[1]..The research work focuses on the route optimization along with the distance, passenger capacity, freight capacity, operational costs, fuel optimization, etc., The data set which is optimized using the favorable algorithm is passed on to the decision making tools for initiation of the decisions.

2. Big data Aviation data

2.1. Large scale aviation data

A study by FAA states that during a year, an aircraft engine generates data equivalent to 20 Terabytes. As of now huge portion of the airline data is not much used for any of the analytics purpose because the data is in unstructured or semi structured form[8, 9]. Primary data sources are such as aircraft data from ACARS, history data from passenger seat bookings, weather data, airline route management system data.

2.2. Big data analytics on aviation data set

Airlines should take initiatives for taking advantage of operational analytics to improve efficiencies and reduce operational costs by optimizing known parameters. By identifying the aircraft operational data assets currently available with algorithmic approach for gathering insights where the airline service organizations better understand the data available for analysis and create service delivery mechanism for actionable insights for increasing profit and eliminating expenses [21, 23].

It is identified that the fuel usage of the aircraft is a vital parameter in the flight trajectory analysis for route profitability optimization.[17,18] Hence, the ultimate goal is to reduce expenses and increase profit by optimizing the route, passengers and other variables which eliminates fuel cost and total distance

2.3. Big data analytics on aviation data set

The objective analysis is performed to optimize the flight trajectory of the aircraft in order to reduce the fuel consumption by optimizing operational costs and distance. The flight trajectory is defined by a simplified description and depends on some of the known or unknown parameters which affect the different phases of the trajectory such as passengers, freights and mails. The flight description variables is analysed over heuristic algorithms such as firefly, bat and cuckoo which is constructed using PL/SQL code and the different parameters vary in order to define their influence on the profits over analysed large data set [1, 5,6, 22,33].The results which are obtained show the influence of the variables over total distance and fuel consumption. Finally, all the few gallons of fuel which are saved over optimized routes are important [34]

3. Heuristic methodologiesfor optimization overlarge scale aviation data

We are opting for nature based meta-heuristic algorithm since, heuristics are often problem-dependent, in which we define an heuristics for a given problem. Meta-heuristics algorithms are problem-independent methodologies that can be applied to a broad range of problems for analysis. An heuristic can be like choosing a random element for pivoting in Quicksort. A meta-heuristic knows nothing about the problem it will be applied, it can treat functions as black boxes. We can say that a heuristic exploits problem-dependent information to find a most optimum or best solution to an specific problem, while meta-heuristics are like design patterns, general algorithmic ideas, which can be applied to a broad range of problems.

In this study, the route profitability is optimized using Meta heuristic algorithms such as Firefly algorithm (FA), Bat algorithm (BA) and Cuckoo search algorithm (CSA). Dynamic Programming (DP) using PL/SQLis used to find the expected cost of each route generated by FA, BA and CSA. Results: The objective is to minimize the total expected expense or maximize profit per airliner per route. The fitness value of a airline and route is calculated using DP. In the proposed model, we are using three algorithms in which the initial particles are generated, based on Nearest Neighbor Heuristic (NNH) which deals with the airliners. The algorithm is implemented using PL/SQL and tested with problems having different number of aviation data set from Australian transportation from the year Jan 2009 to Nov 2014. The results obtained are competitive and showed some significant improvement over profit, in terms of execution time and memory usage as well

3.1. Big data analytics on aviation data set

The Firefly Algorithm was based on the idealized behavior of the chemical light flashing characteristics of fireflies under meta-heuristic approach. A discovery by trial and error under reasonable or lesser amount of time is well meant for heuristics.[11,12,20] In this a consistent collection of flights (particle swarm) from a particular source (ports) to several other destinations (foreign ports) are considered.Each flight (particle) knows it own velocity, route distance, source, destination and intensity.Intensity (Attractiveness [nearest feasible flights for swapping and shifting]) is directly proportional to its/distance. However, the fitness (brightness [most feasible allocation]) is computed using the objective function[10, 26, 29,38].

3.1.1 Pseudo code for firefly algorithm for route profitability based on passengers, freights and mails

```
Begin
1) Define objective function for flights:f(a), a = (a1, a2 ......, an);
2) Generate an initial population of flights ai = (a1, a2 ......, an);
3) Formulatethe seat/freight/mail availability (light intensity)I so that it is associated with f(a)(flights)
    (for example, for maximization problems,I ∝ f(a)(availability based on individual airliners)or simply
I = f(a)(mark availability for each airliner)
4)Define absorption coefficientγ(average number of allocation that can be made since, all available parameters cannot be filled at once)
While (number of airliners<MaxGeneration (available destination ports X available source ports))
for i = 1 : n (all n flights)
forj = 1 : n (n flights)
if (Ii > Ij),
        If the same airliner with same destination on the other port has more availability, then,
moveflighti towards j;
(move flight from a to b and carry out allotment then fly to destination c)
end if
  Vary (attractiveness) fitness with route (distance between source and destination) r via exp (−γr);
      Evaluate new solutions and update new availability(light intensity);
Compute profits.
end for j
end fori
    Rank flight routes with profitability and find the current best;
Perform the best allocation and mark it as final.
end while
Display the results.
end;
```

The main update formula for any pair of two flights on different source airports is x_i and x_j is

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

3.2. Bat Algorithm

Bat behaviour uses echolocation method. Some bats have evolved a highly sophisticated sense of hearing in which we are using this methodology for all the flights that will calculate distance for their destination ports. Bats emit sounds that bounce off of objects in their path sending echoes back to the bats, we are using this method to identify the next nearest source ports with availability for used parameters for swapping and shifting and storing these as temporary findings and rank them. From these echoes, the bats can determine the size of objects, how far away they are, how fast they are travelling and even their texture, all in a split second. We are using the same principle about parameter availability and profit calculation. Based on these ranks we are taking the one which is ranked best for each flight[25].

If we idealize some of the echolocation characteristics of microbats, we can develop various bat-inspired algorithms or bat algorithms. In the basic bat algorithm developed by Xin- She Yang (2010a), the following approximate or idealized rules were used

3.2.1 Pseudo code for Bat Algorithm

```
Begin
Define objective function for flights:f(a), a = (a1, a2 ......, an)T;
Generate an initial population of flights ai = (a1, a2 ......, an) and vi;
Define pulse frequency fiat xi
Initialize pulse rates riand the loudness Ai
while (t < Max number of iterations,
Generate new solutions by adjusting frequency, and updating velocities and locations/solutions
If(rand>ri)
Select a solution among the best solutions
Generate a local solution around the selected best solution
```

```
End if
Generate a local solution around the selected solution
End if
Generate solution by flying randomly
If(rand<Ai & f(xi) < f(xn))
Accept the new solutions
Increase r and reduce Ai
End if
Rank the bats and find the current best xn
End while
Finalize the results; end;
```

3.3. Cuckoo Algorithm

The original “cuckoo search (CS) algorithm” is based on the idea of the following: - How cuckoos lay their eggs in the host nests. (Allotting passengers to other airliners based on seat availability) How, if not detected and destroyed, the eggs are hatched to chicks by the hosts [26, 27]. How a search algorithm based on such a scheme can be used to find the global optimum of a function (Finding available spaces across aircrafts and fitting it into the solution for route profitability)[32]

3.3.1Algorithm Sequence

Step1: Generate initial population of n host nests. We are using this method to find flights with available parameters. A candidate for optimal parameters (Identify number of distinct airliners with source and destination)
Step2: Lay the egg in the fk nest. fk nest is randomly selected. Cuckoo’s egg is very similar to host egg. (Allot the passengers and find out availability.)
Step3: Compare the fitness of cuckoo’s egg with the fitness of the host egg. Root Mean Square Error (RMSE) (Compare with similar flights on the nearest source ports and find out most feasible one.)
Step4: If the fitness of cuckoo’s egg is better than host egg, replace the egg in nest k by cuckoo’s egg. (If the other flight has the available space, then move passengers from A to B)
Step5: If host bird notice it, the nest is abandoned and new one is built. (p <0.25) (to avoid local optimization)
Iterate steps 2 to 5 until termination criterion satisfied. (If the remaining passengers are few in number, smaller aircraft could be used for them with low fuel capacity)

3.3.2 Pseudo code for Cuckoo search algorithm

Begin
Define Objective function for number of airliners $f(x), x = (x_1, x_2 \ldots\ldots, x_n)$;
Generate a list of airliners which have availability for seats, freights and mails;
While (1.. max generation)
Get the airliners one by one and compute the allocation;
Evaluate the fitness after allocation F_i
To get the maximum fitness, $F_i \propto f(x_1)$
Once all possible allocations are computed,
Choose the best allocation which gives maximum profitability
If(F_i>F_j) then, replace the allocation to $F_{I;}$
Repeat the allocation steps until allocation with maximum profitability is reached.
Do the allocation for all the n airliners
Allocate the seats, passengers, freights under best solution.
Calculate route profitability
End;

4. Comparison of algorithms and results

The proposed multi-objective firefly, bat and cuckoo search is implemented in PL/SQL to perform route profitability analysis on airline data set gathered from Australian aviation data. Initially we have tested the algorithm outcomes for these three algorithms using aviation data for November 2014 which has 124 records (with 53 Australian ports and 57 Foreign ports). We have performed Big data analysis on aviation data from January 2009 to November 2014 that consists of 30,000 records of distinct aviation ports.

On the available large aviation data set, when we use firefly we observed the intensities and fitness were based on route’s distance from source to destination port. Here, the route optimization is performed by making source airline to pick up from the next nearest starving airport on the source country (For eg: Australia: Sydney to Italy, Queensland to Italy is mapped as Sydney to Queensland and to Italy) and flies to the destination port. The passengers, freights and mails are allotted only based on native airliners, as the native airliners have their own pattern for allocation. This follows the light flashing and mating pattern of fireflies. (For eg: Indian airline passengers are only allotted to Indian airlines and not others)

Parameters	**Original data**	**Firefly**	**Bat**	**Cuckoo**
Month	14-Nov	14-Nov	14-Nov	14-Nov
Year	2014	2014	2014	2014
# Airliners	27	27	27	27
# Australian ports	9	9	9	9
# Countries	32	32	32	32
# Foreign ports	55	55	55	55
Total distance	765696	745398.69	646873	712188
Total Pax Capacity	995113	995113	995113	995113
Total Paxin	865678	865678	865678	865678
Total Freight Capacity	42400	42400	42400	42400
Total Freight in	22557.4	22557.4	22557.4	22557.4
Total mail capacity	12400	12400	12400	12400
Total mails	1638.2	1638.2	1638.2	1638.2
Total Fuel capacity	1301683.2	1301683.2	1301683.2	1301683.2
Total Fuel used	1225113.6	1192637.904	**1034996.8**	1139500.8
Total Income	29900812861	29249682013	**25461304048**	29797861751
Total Expenses	27225855965	26490984885	**22657951619**	27028323820
Total Profit	2860481165	2864478392	**2918265155**	2865026062
Total loss	185524268.9	105781264	**114912726**	95488131
Nett	2674956896	2758697128	**2803352429**	2769537931

Table 1 : Comparison of Original data with Firefly, Bat and Cuckoo Algorithm

In Bat algorithm, we are able to derive most optimum route similar to firefly. Only difference is the route allocation and passenger allocation is made between multiple airliners based on constraint such as departure time and availability. However in firefly allocation happens only to the native airliners. In this the allocation happens only to the airliners/routs that are feasible for allocation.Feasibility depends on route distance, passenger/freight/mail capacities. Not all source ports/airliners and destination ports/airliners are considered [35, 37].

In Cuckoo algorithm, the passengers were shifted to their native and other airliners based on seat availability and demand under constraint as departure time. Such that aircrafts can be utilized to the maximum and the remaining can be moved to small aircrafts if available to reduce flight operational costs [36].

When comparing we found, for the given data set usage of Bat algorithm gives optimum route profitability when compared to others. The allocation happens in terms of seats, freights and mails towards multiple airliners. The comparison between profits under original data set and the heuristics methods such as Firefly, Bat and Cuckoo are shown in Table 1. The essential parameters optimized are the fuel used,income, expenses, profit, loss and the net amountwhich units in million dollars are displayed in the figure1.

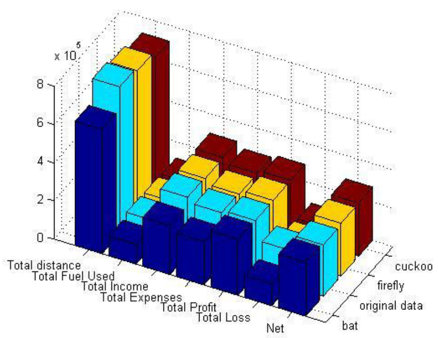

Figure 1: Bat algorithm showing the optimized parameter

5. Analytics based decision support system

Every airline begins with a flight plan which includes route, passengers, freight, mails and other operational data. Over time, small adjustments to each flight plan parameters can add up to substantial savings across a fleet [13,16]. Overall performance of a flight plan of an aircraft can be influenced by many factors which includes accurate flight plans, dynamic route optimization, freight spaces, optimal use of available seat etc., While all airlines use computerized flight planning systems, investing in a higher-end heuristic algorithm based decision support systems and in the effort to use it to use the full capability of big data analytics has significant impact on both profitability and the environment [30, 31].

6. Conclusions

The nature based Meta-Heuristic algorithms will give more optimum results at all levels [11]. The implementation of accurate and algorithm based optimized flight plans can save airlines even litres to several millions of gallons of fuel every year, pretty much without forcing the airlines to compromise their schedules or service. Big data analytics on aviation data helps By varying the routes, shifting passengers, freights, speeds, total distance and amount of departure fuel, an effective flight plan can reduce fuel costs, route distance, overflight costs, time-based costs, and lost revenue from payload that cannot be carried. Such variations are subject to airlines and their airplane performance, weather, allowed route and schedule constraints, altitude structure and operational constraints that are vital parameters needs to be considered. The Bat algorithm yields a better optimized result in par with the other algorithms

7. Future Work

In our future work operating cost, traffic forecasting and airport capacity restriction and several other variables will be considered. There are multiple known and hidden variable factors involving on the aviation data. We will incorporate those to get more optimum results on upcoming works. In aviation we are seeing 3 broad categories of costs in which there is a need for analysis namely the Variable cost- cost that can be saved if a flight is cancelled on short notice[19], the Semi variable cost-Cost that can be saved but with extra effort (reducing operational staff, removing an airplane from the fleet), Fixed cost-Cost that can be saved only through a corporate restructuring the break-down aviation characteristics over costs. Passenger cost are mostly variable, Fuel cost is variable and depend on the airplane flown and the route (route length and fuel cost at the stations)[4], Maintenance is variable (it may be fixed sometimes), which depends on the aircraft flown, the aircraft flight hours and the cycles, Airport landing charges are variable, Navigation over specific route charges are variable, Ground handling of aircraft is variable or semi variable depending on the contract with the handlers, Ownership of Aircraft cost is semi variable, Aviation Crew cost has a variable and a semi variable component, However, Overhead cost is fixed.

Some of the costs of known and hidden flight parameters are not easy to allocate and will be allocated based on block hours (passengers, freights or departures, or ASK;Available Seat Kilometres). Further research can also emphasize the performance comparison of this algorithm with other popular methods for multi-objective optimization In addition; hybridization with other algorithms may also prove the most optimized results.

8. Acknowledgements

Analyzed Data set :Australian government – International airline activity [14]
Lab: Big Data Analytics lab, Apollo Engineering College, Chennai, Tamil Nadu, India

References

[1]Cheikh Kacfah Emani, Nadine Cullot, Christophe Nicolle (2015),Understandable Big Data: A survey Review Article, Computer Science Review, (17): 70-81.

[2] Christian Esposito, Massimo Ficco, Francesco Palmieri, Aniello Castiglione (2015),A knowledge-based platform for Big Data analytics based on publish/ subscribe services and stream processing ,Knowledge-Based Systems,(79): 3-17.

[3] P.G. Kolaitis(2005) Schema mappings, data exchange, and metadata management, Proceedings of the ACM Symposium on Principles of Database Systems (PODS), 90–101.

[4] Megan S. Ryerson, Mark Hansen, James Bonn (2014) Time to burn: Flight delay, terminal efficiency, and fuel consumption in the National Airspace System, Transportation Research Part A: Policy and Practice, (69):286-298

[5] Dilpreet Singh and Chandan K Reddy(2014) A survey on platforms for big data analytics,,Journal of Big Data , (2):8

[6]Veronica L. Foreman,Francesca M. Favaró,Joseph H. Saleh, ChristopherW.Johnson(2015)Software in military aviation and drone mishaps: Analysis and recommendations for the investigation process ReliabilityEngineeringandSystemSafety (137):101–111

[7]Big data : algorithms, analytics, and applications (2015) Chapman & Hall/CRC big data series CRC Press

[8] Peter Berster, Marc C. Gelhausen, Dieter Wilken (2011) Business aviation in Germany: An empirical and model-based analysis, Journal of Air Transport Management (17): 354-359

[9] Hill, S., Provost, F., and Volinsky, C (2006) Network-based marketing: Identifying likely adopters via consumer networks. Statistical Science, (2):256–276.

[10]Yang, X. S., (2010)Firefly Algorithm, Stochastic Test Functions and Design Optimisation, Int. J. Bio-Inspired Computation, (2)78–84.
[11]Yang, X. S. (2008) Nature-Inspired Metaheuristic Algorithms, Luniver Press, UK.
[12] Yang, X. S. (2009)Firefly algorithms for multimodal optimization, Stochastic Algorithms: Foundations and Appplications (Eds O. Watanabe and T. Zeugmann), SAGA 2009, Lecture Notes in Computer Science, 5792, Springer-Verlag, Berlin, 169-178.
[13] Yang, X. S. (2005) Biology-derived algorithms in engineering optimization, in Handbook of Bioinspired Algorithms and Applications (eds S. Olarius& A. Y. Zomaya), Chapman & Hall / CRC.
[14]https://bitre.gov.au/publications/ongoing/international_airline_activity-time_series.aspx
[16]Shilane, D., Martikainen, J., Dudoit, S., Ovaska, S. J. (2008)A general framework for statistical performance comparison of evolutionary computation algorithms, Information Sciences: an Int. Journal, (178):2870-2879.
[17] Jian Chai, Zhong-Yu Zhang, Shou-Yang Wang, Kin Keung Lai, John Liu(2014)Aviation fuel demand development in China, Energy Economics, (46):224-235
[18] Olivier Dessens, Marcus O. Köhler, Helen L. Rogers, Rod L. Jones, John A. Pyle (2014)Aviation and climate changeTransport Policy, (34):14-20
[19]Hideki Fukui, Koki Nagata (2014) Flight cancellation as a reaction to the tarmac delay rule: An unintended consequence of enhanced passenger protection, Economics of Transportation (3): 29-44
[20] Shangyao Yan, Ching-Hui Tang(2007)A heuristic approach for airport gate assignments for stochastic flight delays, European Journal of Operational Research, (180):547-567
[21]Christian Kiss-T´oth, G´abor Tak´acs (2014) A Dynamic Programming Approach for 4D Flight Route Optimization, IEEE International Conference on Big Data, 24-28.
[22] IBM -Websphere MQ.http://www-01.ibm.com/software/integration/wmq/,2012.
[23]D. Fisher, R. DeLine, M. Czerwinski, and S.Drucker (2012), Interactions with Big Data Analytics. Interactions
[24]Elton Fernandesa, R. R. Pacheco (2002)Transport. Efficient use of airport capacity, Res. A-Pol.(36): 225-238
[25]X.-S. Yang (2010) A New Metaheuristic Bat-Inspired Algorithm, in: Nature Inspired Coop-erative Strategies for Optimization (NISCO 2010) (Eds. J. R. Gonzalez et al.), Studies
in Computational Intelligence,Springer, 65-74.
[26]X.-S. Yang, S. Deb (2009) Cuckoo search via L´evy flight,Proc. Of World Congress on Nature &Biologically Inspired Computing (NaBIC 2009),India USA, 210-214
[27] Xin-She Yang (2013) Bat algorithm: literature review and applications, Int. J. Bio-Inspired Computation,(5): 141–149.
[28] Qinwen Yang , Deyi (2015) Comparative study on influencing factors in adaptivemetamodeling, Engineering with Computers ,(31):561–577
[29] X.-S. Yang (2010)Firefly algorithm, L´evy flights and global optimizationResearch and Development in Intelligent Systems XXVI (EdsM. Bramer, R. Ellis, M. Petridis), Springer London: 209-218
[30] Gulsah Hancerliogullari, Ghaith Rabadi, Ameer H. Al-Salem, Mohamed Kharbeche (2013) Greedy algorithms and metaheuristics for a multiple runway combined arrival-departure aircraft sequencing problem, Journal of Air Transport Management (32): 39-48
[31] Atkin, J.A.D., Burke, E.K., Greenwood, J.S., Reeson, D (2008) A meta-heuristic approach to departure scheduling at London Heathrow Airport. Computer Aided Systems of Public Transport.
[32] Momin Jamil (2013) A literature survey of benchmark functions for global optimisation problems, Int. J. Mathematical Modelling and Numerical Optimisation,(4): 2
[33]Lisa Davison, Clare Littleford, Tim Ryley (2014) Air travel attitudes and behaviours: The development of environment-based segments, Journal of Air Transport Management (36):13-22
[34] Zhe L, Chaovalitwongse WA, Huang HC, Johnson EL (2011) Network model for aircraft routing
problem. Transp Sci 45(1):109–120
[35] Suzuki Y, Tyworth JE, Novack RA (2001) Airline market share and customer service quality: a
reference-dependent model. Transp Res Part A 35(9):773–788
[36] Ruther S (2010) A multi-commodity flow formulation for the integrated aircraft routing, crew
pairing, and tail assignment problem. In: Proceedings of the 45th annual conference of the ORSNZ, November 2010
[37] Transportation Research Board (2002) Transportation research E-circular E-C040, aviation demand forecasting: a survey of methodologies. Transportation Research Board, Washington D.C[38]Boeing Current Market Outlook and Airbus Global Market Forecast (2000) excerpted from the British Airways
[38] E. Kasturi, Dr. S. Prasanna Devi, S. Vinu Kiran., Airline route profitability analysis on Bigdata using Firefly Algorithm. Aust. J. Basic & Appl. Sci., 9(10): 313-320, 2015