Research on aircraft landing schedule using opposition-based genetic algorithm with Cauchy mutation

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Abstract: Optimal scheduling of airport runway operation plays a significant responsibility in the aircraft transportation. Arrival runways are a crucial resource in the air traffic system. Arrival delays encompass an immense impact on airline operations in addition to cost. An imperative responsibility is the planning of airport operations like arrival and departure of aircraft. At this juncture, this paper describes the technique of the execution time in addition to the penalty cost of the every aircrafts. These experimentations demonstrate whenever aircrafts landing on the runway in the mean while no congestion on to facilitate particular path, if it is happening subsequently it seems to be problematic. In order towards eradicating these problems, neural network and genetic algorithms through Cauchy mutations are utilised in the direction of eradicating the congestion occur during the runway as well as in addition to proposed technique towards reducing the penalty cost to be charged.

Keywords: artificial neural network; ANN; aircraft selection; OGACM; runway selection; scheduling.

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1 Introduction

Over the past few decades, air traffic has experienced a remarkable expansion. Here the paper shows to study the problem of landing aircraft at a busy airport. Specified a set of aircrafts in the radar horizon of an air-traffic controller (ATC), the problem is one of determining a landing time intended for every aircraft so as to every plane within this ATC horizon land within a pre specified landing time window and such that landing separation criteria specified meant for every pair of aircrafts in this horizon it is remained.

The number of approaching flights surpasses the airport capacity; a number of these aircraft cannot be landed on its perfect landing time. There is a cost mostly on the waste of fuel intended for every aircraft flying more rapidly than its generally cost-effective speed. Airlines moreover experience the different costs meant for delays of different aircrafts. Consider the aircrafts within the radar range (or horizon) of an ATC at an airport. In general, the ATC will be in charge of determining approach paths, runway allocation along with landing times of numerous aircrafts in the radar horizon. Every aircrafts encompass a preferred landing time as well as earliest in addition to latest probable landing times. In addition, there are aerodynamic considerations so as to arise since the turbulence created by landing aircraft. These considerations inflict a constraint that the landing time among two aircraft pairs in the horizon has to be greater than a few minimum intervals. This minimum separation is dependent on the aircraft types and might be different for different pairs of aircraft on the horizon. The problem of assigning towards every aircraft at landing time in the mean time all aircrafts land as close as possible towards their preferred landing time determination be called the aircraft landing problem (ALP). There are numerous variants of the ALP and lots of approaches intended for solving it.

Specified fixed aircraft routes as well as a set of work system distinct with the collective agreement, the airline subsequently builds crew rotations or pairings through solving a crew scheduling problem. In general, conditions, a crew pairing is a succession of duty and rest periods with the intention of usually lasts among 2 and 5 days. The intention of the crew scheduling problem is to determine a minimum-cost set of pairings as a result that each flight leg is allocated a qualified crew in addition to each pairing satisfies the set of appropriate work rules (Mercier and Soumis, 2007). Two different approaches in the direction of model this problem is recognised. The ostensible ground delay program considers the capacity during a time period specified and followed by flights allocated to arrival slots (fixed length time intervals). This assignment is done in instruct of the original schedule (Moghaddam et al., 2012). The controller ought to create a right separated flow of aircraft en route for the runway. To sustain the safety, a minimum separation among landing aircraft is necessary. This separation depends on the weight categories of the aircraft. In the solitary runway circumstances the landing succession adopted in favour of incoming aircraft is frequently determined in a first-come first-served (FCFS) manner. While multiple runways are present, the FCFS manner is as well frequently used such to facilitate aircraft land on their allocated runway, in the similar order they appeared in the radar range.

A problem concerning a mix of takeoffs and landings are on the similar (or on different) runways. In addition, here the paper, concerns through the static case of scheduling aircraft landings. Statistical analysis of aircraft arrivals at numerous foremost airports in the USA encompasses with the intention of the distribution of times among the estimated arrival times of successive aircraft (estimated while the aircraft are 100 miles as of their final destinations) is nearly exponential in temperament (Deep and Thakur, 2007). However, frequently in applications the operational environment revolutionise, typically since time passes new information, formulates it essential to amend the preceding decisions that have been made. In those kinds of circumstances are dynamic in the intelligence so as to planned decisions frequently have to be revisited as the operational environment changes (Pratama et al., 2015a). Due to its complexity, it is difficult to find the optimal solution towards the problem in most cases. Consequently, it draws important attention as of dissimilar scientific communities by means of numerous research studies carried out on modelling in addition to developing algorithms to increase capacity at an airport (Pratama et al., 2015b).

Moreover, in this paper, it is organised as follows: the second section presents literature re-examines based on existing work for aircraft scheduling problems. Third section presents a methodology based on artificial neural network (ANN) and opposition-based genetic algorithm (OGA) intended for the selecting runway of the aircrafts. Fourth section presents the results and analyses relating to the proposed technique of the aircraft scheduling. Here it showed the improvement in the OGA through neural network optimisation presented in Section 3.

2 Literature review based on existing work

In 2015, Nithyanandam encompasses the actual time reducing the penalty cost of aircraft landing using opposition particle swarm optimisation through Cauchy mutation. It is to model the ALP in addition to, it utilises the aircraft selection, precedence restrictions, restricting the number of landings and takeoffs in a specified time period, runway workload balancing. Since the results of neural network and genetic algorithms (GA) were utilised to eliminate the congestion occur on the runway furthermore, it minimises the penalty cost to be charged. It was accomplished that the penalty cost was merely depends on time. Subsequently, that the conserved time certainly reduced the penalty cost.

Nithyanandam (2014) encompasses that the authentic time aircraft landing schedule through an endeavour towards optimising the similar with GA through the reduced penalty cost. It was to model the ALP and it was used the aircraft selection, precedence restrictions, restricting the number of landings and takeoffs in a specified time period, runway workload balancing. From the consequences, neural network and GAs were utilised in the direction of eradicating the congestion occur on the runway in addition to its also minimise the penalty cost to be charged. It was completed with the intention of the penalty cost was merely depends on time. As a result, that the conserved time was positively minimised the penalty cost.

Juang et al. (2008) presented an intellectual aircraft automatic landing controller with the intention to use recurrent neural networks (RNN) through GAs to improve the performance of the conventional automatic landing system (ALS) and direct the aircraft in the direction of a safe landing. Real-time recurrent learning (RTRL) was applied to train the RNN that uses gradient-descent of the error function through respect to the weights in the direction of performing the weights updates. Convergence analysis of system error was offered. The control scheme utilises five crossover methods of GAs headed for search optimal control parameters. A simulation demonstrates that the proposed intelligent controller encompasses enhanced performance than the conventional controller.

Moghaddam et al. (2012) scrutinise the ways of landing aircraft through the least waiting time in time windows beneath crucial conditions, such as the closest time of landing to the target times meant for every aircraft or the minimum time of landing the aircraft. As a result, they countenance by means of two conflict intentions, specifically minimising the total cost of the divergence from the target times and minimising the completion time of the landing succession. To resolve a problem, they use a fuzzy programming approach with an estimator intended for landing the sequence of aircrafts. The results are compared through actual landings.

Scheduling aircraft landing is a complex task encountered with most of the control towers. Here in this paper, the ALP in the multiple runway case. Bencheikh et al. (2011) include a mathematical formulation of the problem through a linear as well as nonlinear objective function. In the second part, they consider the static case of the problem where the entire data are recognised in advance as well as obtainable a proposed heuristic intended for scheduling aircraft landing on a solitary runway, the proposed heuristic was integrated into an ant colony algorithm towards solving the multiple runway case.

The ground staff workload was extremely large while the aircraft landings and takeoffs at the airport. A study narrates in this paper that a landing time in the ACT. In Boysen and Fliedner (2011), to sustain this decision problem through suited optimisation approaches includes a long lasting tradition in operations research. The paper on hand presents three novel objectives intended for the ALP, which endeavours at levelling the workload of ground staff by consistently spreading:

1 number of landed passengers
2 landings per airline
3 number of landed passengers per airline in excess of the planning horizon.

Mathematical models through complexity results were developed along with exact and heuristic solution procedures are presented.

Hsu et al. (2011) developed a stochastic dynamic programming model to optimise airline decisions concerning purchasing, leasing, or disposing of aircraft over time. Grey topological models by Markov chain were engaged to predict passenger traffic and capture the randomness of the demand. The consequences demonstrate with the intention of severe demand fluctuations would drive the airline towards lease rather than to purchase its aircrafts. Here the proposed technique would consent to greater flexibility in fleet management and allows for matching short-term variations in the demand. It endows with a useful reference meant for airlines in their replacement decision-making process through captivating keen of consideration the fluctuations in the market demand and the status of the aircraft.

Liu et al. (2011) presented a technique to decrease the flight delays and ease the airport congestion, a space-time network taxi scheduling model integrates the three types of conflicts was used. In the model, the aircraft taxiing schedule problem was transformed into a multi-commodity network model, and the genetic-annealing algorithm was intended to resolve the problem. The simulation case demonstrates with the intention of optimised schedule, results considerably reduced the total taxiing time by 586 seconds of 17 flights compared through FCFS strategy and avoided the potential flight conflicts, which significantly enhanced airport operational efficiency. In addition, genetic-annealing algorithm weight out the standard GA in convergence rate along with solution efficiency.

3 Opposition-based learning and genetic algorithm with Cauchy mutation

The perception of OBL method is originated upon a familiar observation so as to, in actual life, people oppose solitary in additional. The strengths and weaknesses of these opposing ones are relative, i.e., the opposition of a weak person is strong relative to him. Correspondingly traits are frequently opposite towards every other within the similar way opposition of a weak trait has been frequently strong one. In OBL method, it generates a second set of solutions which is opposite of the original solution set so to facilitate the probability of choosing improved solutions can increase. Here the paper proposes an implementation strategy of opposition-based learning method intended for the GA. In proposing this technique, we introduced gene excitation as a fourth operator along by means of elitism, crossover and mutation. Gene excitation is used towards elevating any specific solutions based on probability. The opposite of a number x can be calculated using the subsequent equation.

$$X_i^1 = a_i - b_i - x$$

This opposite vector will be calculated using the boundaries $[a_i; b_i]$.

Figure 1 Calculating opposition of a point

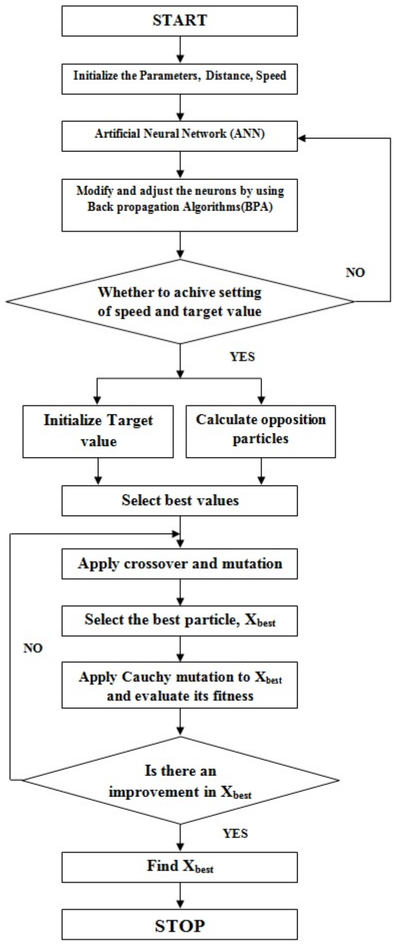
Therefore, opposition of point = (maximum value – minimum value) – initial solution.

The GAs suffer a lot due towards their slow convergence rate, mostly due to the evolutionary nature of these algorithms. This paper presents an innovative mutation scheme meant for OGAs.

Correspondingly, an opposite position in the search space is able to define as a point where the entire dimensions of this point are replaced with their respective opposites. Any point in hyper dimensional space encompasses a unique opposite point. The solution sets intended for a specified optimisation problem encloses a multiple number of solutions. The population of a GA is composed of chromosomes. A chromosome can be viewed as a potential solution along with a set of solutions (set of chromosomes) for the specified problem.

Create innovative population as of children and parent population opposite of a chromosome through Cauchy Mutation can be distinct in a like manner.

Figure 2 Overall flowchart timing analysis stem with neural network



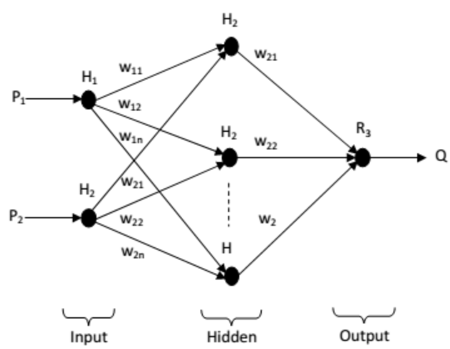
4 Cauchy mutated GAs

The use of mutation operation is not innovative in the field of GAs. Its major aim is to initiate a small perturbation in the population from time to time so as to sustain its diversity. Most of the times the mutation operation is applied according to a number of fixed probabilistic rules. Also the number of times mutation determination takes place is also predefined. In the past few years mutation operations based on dissimilar probability distributions (like normal, Gaussian, Cauchy, etc.) have become quite popular. The present study attempts to the flowchart of OGACM is given in Figure 2.

5 Methodology

According to this technique aim is reducing the penalty cost of aircrafts. So, here it is been utilise the neural network and opposition GA. In neural network optimisation intended for finding the optimised set of timings along with opposition GA with cauchy mutation is meant for optimised runway and aircraft selection.

Figure 3 Artificial neural network



An ANN, it is made up of lot artificial neurons in addition to each of input encompasses the own weight associated through it. An artificial neuron is a device through a lot of inputs and one output. The neuron has two modes of operation; the training mode and the testing mode. In the training mode, the neuron can be trained to fire (or not), intended for particular input patterns. In the testing mode, while a taught input pattern is detected at the input, its associated output becomes the current output. Here output is produced where the input is speed and distance applied in the direction of the neural network.

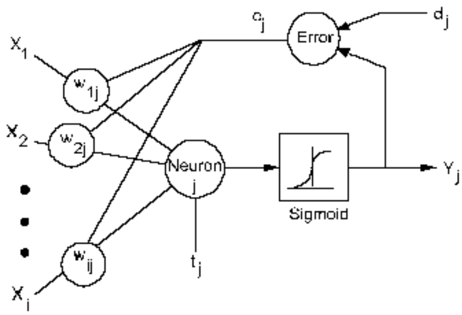
$$R_b = \sum \left(P_a \cdot W_{ab} \right) \tag{1}$$

$$Q_b = F_{th} \left(R_b + t_b \right) \tag{2}$$

Equation (1) implements the combined operation of the neuron and equation (2) implements the firing of the neuron.

By using back propagation algorithm.

Figure 4 Neuron weight adjustment



This corrective procedure is called back propagation (hence the name of the neural network) and it is applied continuously and repetitively intended for every set of inputs and corresponding set of outputs produced in response to the inputs. This process continues so long as the individual or total errors in the responses exceed a specified level or until there are no measurable errors. At this point, the neural network encompasses learning the training material in addition to stop the training process and use the neural network to produce responses to new input data.

Back propagation starts at the output layer by the following the equations:

$$W_{ab} = W_{ab}^{*} + LR \cdot e_b \cdot P_a \tag{3}$$

$$e_j = Q_b \cdot (1 - Q_b) \cdot (d_b - Q_b) \tag{4}$$

$$e_b = Q_b (1 - Q_b) \cdot \sum (e_c \cdot W_{bc}) \tag{5}$$

$$W_{ab} = W_{ab}^{*} + (1 - M) \cdot LR \cdot e_b \cdot P_b + M (W_{ab}^{*} - W_{ab}^{**}) \tag{6}$$

where

a, b each of inputs and layers respectively

P_a a^{th} input of network

W_{ab} established weight

R_b internal value of the operation

t_b established threshold value

Q_b resulting output

F_{th} activation function

LR learning range

e_b error

M momentum factor.

The technique distance in addition to speed are variability and to find the time of the aircraft travelling on the runways. Initially, all of initialised variability parameters of distance and speed. Calculate the hidden layer weight value of the every input and output layers. To assign the target value intended for process going on the particular target value. Mainly the closed loop systems have the error value that determination will affect the output of the system. So, it is unnecessary output for the desired output so it will be previously rectified. Subsequently modify and adjustment to the distance and speed values for the desired timings. If the variable values are extremely high compared to a threshold value subsequently the process moved to again input to calculate the hidden layers, if low that value is moved to the GA input. It is an optimised solution of the ANN output. This optimised set of timings is fed to the GA with Cauchy mutation.

6 Optimisation process with the aid of GA

6.1 Generation of chromosome

The generation of chromosomes is the function of the randomly generated set of chromosomes (set of genes). Proposed technology to collect all the scheduling time, the ANN's output for allocating the separate runway, for every aircraft landing and takeoff operation.

6.2 Fitness computation

Fitness computation is the most excellent way to find the optimisation solution on the chromosomes. In proposed technology to apply the entire timing to the fitness computation, in this value should mainly based on the weight factor of the all chromosome timings.

$$\sum_{a=0}^{N-1} \alpha_b \frac{1}{1+\exp \sum_{a=0}^{N-1} (1 - p_a \beta_b)} = T_t \tag{7}$$

$$\sum_{a=0}^{N-1} \alpha_b \frac{1}{1+\exp \sum_{a=0}^{N-1} \left(1 - \left(T_t - \left(\sum_{i=0}^{n-1} p_{n_a} \right) \right) \beta_b \right)} = T_s \tag{8}$$

α_b, β_b weights

T_t total time taken for the flight to reach the destination point

T_s signal time when the waiting flight gets the signal.

p_a input time parameters.

In the parameters of speed and distance of the every aircrafts is applied to it, this determination produces the output. This is the time to take the flight entirely travelled on the runway. At that time to find the aircraft cross the selecting point of the total distance on the runway that is mentioned in the above equation. In the rest of the distance might be determined from dissimilarity between total time and selecting point distance. That refers the signal time of the holding flight. In order to reduce the emergency landing penalty cost the remaining distance to travel flight timings. With the technique penalty cost is reduced compare to the existing techniques.

6.3 *Selection of best chromosomes*

In all the chromosomes are producing the dissimilar fitness value. Having to select the minimum value of the fitness value chromosomes. They are known as parent chromosomes. In proposing technology to utilise the best timing chromosome need to select the merely minimum fitness value intended for every aircrafts both operations.

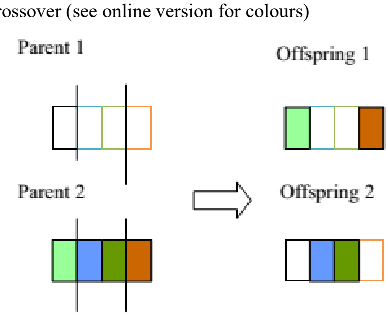
6.4 *Crossover*

Reproduction contains the crossover and mutation operation. The crossover operation is having numerous methods to produce the offspring. They are one point, two points, uniform and arithmetic crossover.

6.5 *Two-point crossover*

A crossover operates with the intention of randomly selects a crossover point within a chromosome subsequently interchange the two parent chromosomes among these points to produce two innovative offspring. While recombined the chromosomes avoids genes at the head and genes at the tail of a chromosome are always split.

Figure 5 Two point crossover (see online version for colours)



Use the Cauchy mutation operator as a local search strategy. Opposition-based genetic algorithms with Cauchy mutated (OGACM) starts similar to the basic GA algorithm by means of the similar mutation equation as specified in the previous section to generate the perturbed mutant vector. The process of generating the trial vector and selecting the fitter candidate intended for the next generation is also similar as that of a basic GA algorithm. Once the selection process is complete, i.e. at the end of each iteration search the neighbourhood of the best (or global best) particle says X best with the CM operator. If subsequent to mutation the solution quality is improved, then it is applied again to observe if the solution can be enhanced any further. This procedure continues till keep getting improved solution. In case there is no improvement in the solution, then the algorithm moves to the next iteration. At the end of each iteration-mutation is defined as:

$$x'_{best} = X_{best} + C^* [X_{r1} - X_{r2}]$$

where X_{best} is the global best particle, C is the Cauchy, distributed random number and r_1, $r_2 \in \{1, 2, \ldots, \text{NP}\}$ are randomly chosen integers, dissimilar from each other and in addition to dissimilar as of the global best particle.

Here it is being used the two point crossover for further operation. In this technique this crossover and mutation operation having the runway selection, aircraft selection, assigned and modifying the aircraft timings and aircraft selection. In runway selection is the significant operation of the airport radar control system with the intention of it is only providing the information for every aircrafts. In this radar system, it is usually covered above 300 km range that is analysed whenever one aircraft is within the range that is communicating with the aircraft system. If the speed of the aircraft slows the aircraft control system to ensure if any aircrafts are detected within the radar range, then assigned the timings and runway intended for that aircraft. Assign and adjust the timings are happening under the crossover and mutation area. If there are no more aircraft is obtainable in this area, there is no problem occurred in aircrafts both operations.

6.6 Objective function

Here to consider two possibilities that, first the landing time of aircrafts is fundamentally fixed and second, that this is not the case and every aircraft encompasses to be treated separately so as to minimise the movements in excess of the entire landing bank. The objective is to minimise the weighted sum of deviations of landing time as of the target time; in other words, aircraft should land close to the target time.

$$\min Z = \sum_{a=1}^{P} (g_a \times e_a + h_a \times l_a) \tag{9}$$

Subjected to

$$E_a \le A_a \le L_a \qquad \forall a \in P_s \tag{10}$$

$$A_b \ge A_a + S_{ab} - (L_a + S_{ab} - E_b) \times d_{ba} \qquad \forall a, b \tag{11}$$

$$e_a \ge T_a - A_a \qquad \forall a \in P_s \tag{12}$$

$$0 \le e_a \le T_a - E_a \qquad \forall a \in P_s \tag{13}$$

$$l_a \ge A_a - T_a \qquad \forall a \in P_s \tag{14}$$

$$0 \le l_a \le L_a - T_a \qquad \forall a \in P_s \tag{15}$$

$$A_a = T_a - e_a + l_a \qquad \forall a \in P_s \tag{16}$$

$$d_{ab} + d_{ba} = 1 \qquad \forall a, b \quad a \ne b \tag{17}$$

$$d_{aa}, s_{bb} = 0 \qquad \forall a \tag{18}$$

$$A_a \geq 0 \quad \text{and} \quad d_{ab} \in \{0,1\} \tag{19}$$

$$A_a, e_a, l_a \geq 0 \qquad \forall a \in P_s \tag{20}$$

Constraint (2) ensures that every aircraft appearing in P_s lands within its time window. Constraint (3) is the time of landing every aircraft. Constraints (4) and (5) ensure that a_x is at least zero and the time dissimilarity among T_a and x_a, and the majority of the time difference between T_a and E_a. Constraints (10) and (11) are similar equations for b_a. Equation (12) Relates the landing time (x_a) to the time aircraft a lands prior to (a_a), or after (b_a) the target time (T_a), equation (13) Ensures that an aircraft can land in every sequence. Equations (14) and (15) are necessary constraints. Unlike the first model, the second minimises in general time over which the aircrafts land; this can cause an increase in deviations among the landing times and target times for aircraft. Equation (16) is the objective function minimising the costs of landing aircraft. Equation (17) satisfies the landing time frame for aircraft (a) through earliest and latest time of landing. Equation (18) expresses the time of landing every respective plan. Equation (16) ensures that the landing time ought to be lower than the completion time. Equation (17) ensures that the aircraft can land one time in every sequence. Equations (19) and (20) are necessary for estimation.

$$\min Z = C_{\max} \tag{21}$$

$$E_a \leq A_a \leq L_a \qquad \forall a \in P_s \tag{22}$$

$$A_b \geq A_a + S_{ab} - (L_a + S_{ab} - E_b) \times d_{ba} \qquad \forall a, b \tag{23}$$

$$C_{\max} \geq A_a + S_{ab} \qquad \forall a \tag{24}$$

$$d_{ab} + d_{ba} = 1 \qquad \forall a, b \quad a \neq b \tag{25}$$

$$d_{aa}, s_{bb} = 0 \qquad \forall a \tag{26}$$

$$A_a \geq 0 \quad \text{and} \quad d_{ab} \in \{0,1\} \tag{27}$$

where

A_a landing time for aircraft a ($a \in P$)

e_a how soon aircraft a lands before T_a ($a \in P$)

l_a how late aircraft a lands after T_a ($a \in P$)

g_a unit costs for aircraft a landing earlier than the target time

h_a unit costs for aircraft a landing later than the target time

S_{ab} separation time between aircraft a and b, where a lands before b

T_a target time for aircraft a

E_a earliest possible time of landing aircraft *a*

L_a latest possible time of landing aircraft *a*

$$d_{ab} = \begin{cases} 1, & \text{if aircraft lands before} \\ 0, & \text{otherwise} \end{cases}$$

$C_{\max}$ completion time

$[E_a, L_b]$ predetermined landing time window for aircraft *a*.

6.7 Select optimised timings

$$\sum_{a=0}^{N-1} \alpha_b \frac{1}{1+\exp\sum_{a=0}^{N-1}(1-p_a\beta_b)} = T_{t(opt)} \tag{28}$$

$$\sum_{a=0}^{N-1} \alpha_b \frac{1}{1+\exp\sum_{a=0}^{N-1}\left(1-\left(T_t-\left(\sum_{i=0}^{n-1} p_{n_a}\right)\right)\beta_b\right)} = T_{s(opt)} \tag{29}$$

$T_{t(opt)}$ optimised total time taken for the flight to reach the destination point

$T_{s(opt)}$ optimised signal time, when the waiting flight gets the signal.

In this section output is in general optimised timings intended for the every aircraft operation was computed. This is the optimised solution for proposed technique. Based on optimise timings, the penalty cost has evaluated. This is clearly explained in the future section.

6.8 Computing penalty cost

Penalty cost depends on the timings (delay and past landing flight timings). The most important reason intended for collecting the cost is unnecessary usage of fuel. Even a single unit is reduced in timing factor is also useful intended for reducing penalty cost.

$$\text{Delay time} = \text{Scheduled time} - \text{Flight arriving time}$$

$$\text{Penalty cost} = \frac{\text{time}}{1\text{ unit}} * M_c$$

M_c = Money charged

1 unit = 20 seconds

1 unit charge = (₹ 2,180)

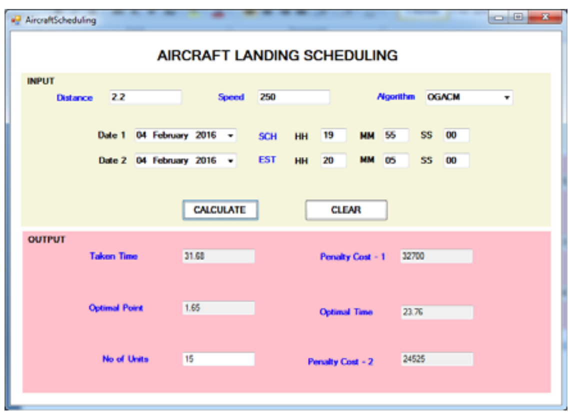
Table 1 OGACM algorithm results

S. no.	*Flight name*	*Distance*	*Speed*	*SCH*	*EST*	*OP*	*OT*	*TT*	*PC1*	*PC2*	*No. of units*
1	G8 320	2.2	251.8	13:10	13:21	1.65	23.5	31.4	39,240	29,430	18
2	SG 3455	2.5	257.4	13:15	13:19	1.87	26.2	34.9	0	0	0
3	9W 326	2.55	259.2	13:40	13:46	1.91	26.5	35.4	6,540	4,905	3
4	6E 189	2.5	275.9	17:10	17:14	1.87	24.4	32.6	0	0	0
5	9W 308	2.4	275.9	17:30	17:24	1.8	23.4	31.3	6,540	4,905	3
6	SG 161	2.5	277.8	17:45	17:21	1.87	24.2	32.3	124,260	93,195	57
7	6E 169	2.3	259.2	18:05	17:50	1.72	23.9	31.9	65,400	49,050	30
8	9W 362	2.3	259.2	19:55	19:34	1.72	23.9	31.9	104,640	78,480	48
9	6E 129	2.25	250.0	20:00	19:58	1.68	24.2	32.3	0	0	0
10	UK 979	2.3	259.2	20:20	20:18	1.72	23.9	31.9	0	0	0

7 Results and discussion

This section discussed the experimental results of proposed method intended for reducing at the penalty cost using opposition GA by means of Cauchy mutation. Proposed technique produced the optimisation at the penalty cost along through speed and distance of the aircrafts. To reduce the penalty cost here utilised OGACM-based optimised technique. Whereas aircraft is landing on the runway, primarily need to calculate the total time taken intending for the aircraft to arrive at the destination as of its source once the aircraft reaches its destination and subsequently the controlling unit gives the signal to the subsequently flight to reach on the particular runway. For this procedure encompasses pick the optimal point solution intended for minimising the penalty cost and to minimise the conjunction to be occurs. For so as to pick the particular distance of the total distance on the runway, then calculate the aircraft crossing the particular distance of the runway. If the time constrain after the optimised pick point is nearly half the time than the source to optimal point distance. If this condition satisfies then the controlling unit allows the next flight to land on the particular runway. This probably reduces the penalty cost as well as conjunction to be occurring between two adjacent flights.

Figure 6 Testing application tool (see online version for colours)



7.1 Normal scheduling process

Figure 7 expressed as the normal timings of the each aircraft to landings on the particular runway.

After showing graphs, X-axis comprise of distance and Y-axis speed time and cost. The combination of these three clearly shows that the speed, time and penalty cost incorporate to each other and their relation also clearly defined in Figure 7.

Figure 7 Normal scheduling process (see online version for colours)

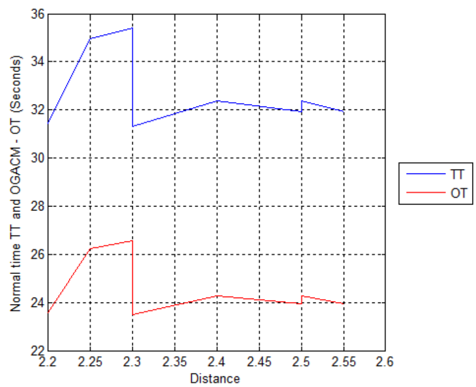
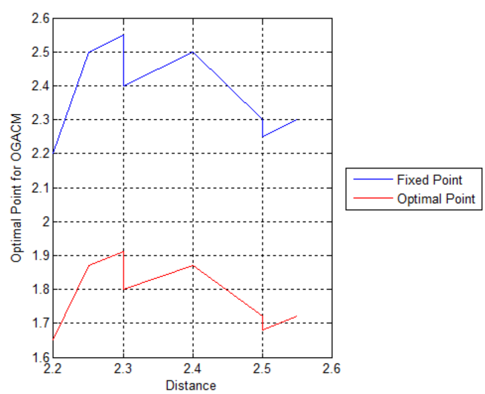


Figure 8 Optimised solution for each aircrafts (see online version for colours)



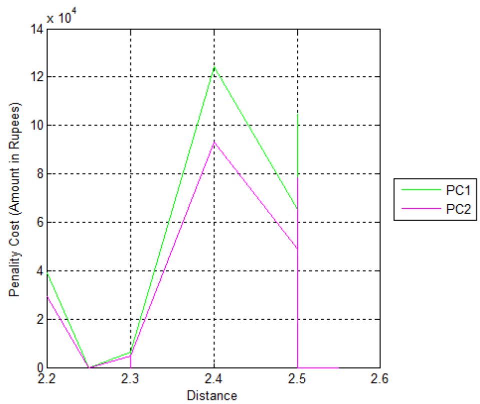
The optimised solution graph (Figure 8) considers the optimised pick point distance as x-axis and speed, time and penalty cost are in the y-axis. This graph gives the explanation the variation of penalty cost on a variety of optimised peak point. Among the entire the optimised point first and seventh point gets lower penalty cost. Whereas the sixth getting, higher penalty cost. Subsequently, by analysing this graph conclude so as to the penalty cost merely depends on time. Consequently that the conserved time determination certainly reduced the penalty cost.

7.2 Penalty cost

In this penalty cost estimation graph, the normal computation of penalty cost is compared by means of the proposed optimal point detection estimated graphically; this shows that the proposed technique is enhanced than the normal free running penalty cost computing.

The penalty cost graph (Figure 9) is plotted intended for runway distance and penalty cost. In Figure 9, blue colour marked line demonstrates the penalty cost intended for free running aircraft, and the red colour shows that the penalty cost computed intended for optimal point detection. This graph clearly shows that the proposed technique is betted in addition to reduce the penalty cost.

Figure 9 Optimised penalty cost (see online version for colours)



8 Conclusions

The existing technique usually viewed on the aircraft landings and flight delay timings this delay and landing time in sequence encompasses not be said in the existing technique. Consequently, the proposed technique provides the solution for landing timings of the aircraft along through the midpoint selection. Here utilise ANN intended for generating data set and OGAs through Cauchy mutation for optimisation. In proposed work, the ultimate aim is to eradicate the congestion occur among the emergency and normal landing. While the emergency occurred in the other targeted flight timing at that time conflict occur, in this case penalty cost is charged for the emergency flight. OGA is used as a competitor algorithm in the direction of comparing the results of the proposed algorithm. The results demonstrate with the intention of the proposed method outperforms GA and OGA for generally of the test functions. In order to minimise the penalty cost proposed technique is further efficient to minimise the penalty cost.

References

Bencheikh, G., Boukachour, J. and Alaoui, A.E.H. (2011) 'Improved ant colony algorithm to solve the aircraft landing problem', *International Journal of Computer Theory and Engineering*, Vol. 3, No. 2, pp.224–233.

Boysen, N. and Fliedner, M. (2011) 'Scheduling aircraft landings to balance workload of ground staff', *Computers & Industrial Engineering*, Vol. 60, No. 2, pp.206–217.

Deep, K. and Thakur, M. (2007) 'A new crossover operator for real coded genetic algorithms', *Applied Mathematics and Computation*, Vol. 188, No. 1, pp.895–911.

Liu, Q., Wu, T. and Luo, X. (2011) 'A space-time network model based on improved genetic algorithm for airport taxiing scheduling problems', *Procedia Engineering*, Vol. 15, No. 5, pp.1082–1087.

Lughofer, E., Cernuda, C., Kindermann, S. and Pratama, M. (2015) 'Generalized smart evolving fuzzy systems', *Evolving System*, Vol. 6, No. 4, pp.269–292.

Mercier, A. and Soumis, F. (2007) 'An integrated aircraft routing, crew scheduling and flight retiming model', *Computers & Operations Research*, Vol. 34, No. 4, pp.2251–2265.

Mercier, A., Cordeaub, J.F. and Soumis, F. (2005) 'A computational study of Benders decomposition for the integrated aircraft routing and crew scheduling problem', *Computers & Operations Research*, Vol. 32, No. 8, pp.1451–1476.

Moghaddam, R.T., Panah, M.Y. and Radmehr, F. (2012) *Scheduling the Sequence of Aircraft Landings for a Single Runway Using a Fuzzy Programming Approach*, No. 6, pp.1–4.

Nithyanandam, C. (2014) 'Study of real time aircraft landing schedule with an attempt to optimize the same using non-traditional algorithms', *Journal of Theoretical and Applied Information Technology*, Vol. 65, No. 3, pp.642–632.

Nithyanandam, C. (2015) 'Minimizing the penalty cost of aircraft landing using opposition particle swarm optimization', *International Journal of Applied Engineering Research*, Vol. 10, No. 71, pp.268–279, ISSN 0973-4562.

Pratama, M., Anavatti, S.G., Joo, M. and Lughofer, E.D. (2015a) 'pClass: an effective classifier for streaming examples', *IEEE Transactions on Fuzzy Systems*, Vol. 23, No. 2, pp.369–386.

Pratama, M., Sreenatha, Anavatti, G. and Lu, J. (2015b) 'Recurrent classifier based on an incremental meta-cognitive-based scaffolding algorithm', *IEEE Transactions on Fuzzy Systems*, Vol. 23, No. 6, pp.2048–2066.