A Multiobjective Optimization Approach for Reducing Air Traffic Collision Risk

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***Abstract*—Air transport contributes significantly to the globalization and world economic. With the increasing demand for both passengers and air cargo, future airspace may encounter unprecedented traffic pressure. To ensure the flying safety is always the paramount commitment of air transport. In the face of increasing traffic demand, it is pertinent to investigate how to reduce en-route collision risk without compromising the traffic demand. In this paper, we propose a multiobjective optimization based method to reduce the technical vertical risk (TVR) by controlling en-route air traffic speed. The suggested method simultaneously optimizes two objectives. The first one aims to minimize the TVR while the second tries to minimize the traffic delay. As the modeled optimization problem is concave and the two objectives conflict with each other, we therefore introduce two well-known multiobjective evolutionary algorithms named NSGA-II and NSGA-III and modify some of their operators to solve the proposed optimization problem. Finally, we carry out experiments on sixteen real-world daily traffic sample data that cover en-route flights within the Singapore flight information region (FIR). Experiments demonstrate that by optimizing the proposed problem using the introduced algorithms we obtain a set of speed control suggestions each of which can reduce the TVR for the Singapore FIR. This work will contribute both to strategical and tactical air traffic management as the aviation players can make the preferred choices based on the solutions yielded by the introduced algorithms.**

I. INTRODUCTION

Air transport is an indispensable part of the national as well as the international transportation systems due to its massive contribution to the domestic and international economics, especially for countries like USA and China. The air transport industry, including airlines, and its supply chain, are estimated to support respectively US $641 billion and $78 billion of GDP in the United States and China for 2019 [1].

The year 2020 was battered by the COVID-19 pandemic [2]. The COVID-19 pandemic has confined air travel for a long time. It is expeced that the air traffic demand will bounce back when the pandemic is eliminated and may double to 7.8 billion in 2036 [3], which poses unprecedented challenges to existing air traffic systems (ATSs). An en-route airspace, one of the critical components of an ATS, is the controlled airspace where the climb, cruise and descent phases of an aircraft take place. For the sake of safety considerations as well as to increase airspace capacity, an en-route airspace is widely organized to be a reduced separation minimum (RVSM) airspace which has a layered structure and is vertically separated by 1000 feet. As a consequence, a RVSM airspace has a maximum capacity limitation. The imbalance between the airspace capacity and the traffic demand can risk an airspace reaching its bottleneck for accommodating the traffic demand in the near future if effective air traffic management (ATM) protocols are not available till then.

In order to better improve existing ATSs in terms of efficiency, safety, greenness, etc., famous projects such as SESAR (Single European Sky ATM Research), NEXTGEN (Next Generation Air Transportation System) were commissioned. Many ATM initiatives also have been put forward, and amongst which are air traffic flow management (ATFM) [4], ground delay program (GDP) [5], arrival manager (AMAN) [6], departure manager (DMAN) [7], collaborative decision making (CDM) [8], etc. Note that with regard to the safety concerns, the above mentioned ATM protocols mainly deal with air traffic conflict detection and resolution CD&R [9] while very few attention is paid to the en-route traffic collision risk. An en-route air traffic controller (ATCo) monitors all the traffic within a sector, the basic unit of an airspace. During the cruise phase, an aircraft may deviate from the assigned flight level and route due to communication, navigation and surveillance errors as well as maneuvering requirements to avoid convective weather. The flight path deviation of one aircraft could cause conflict against other aircraft. If a pair of aircraft is detected to conflict with each other, then the ATCo in charge will contact the pilots and give them maneuvering instructions, and the conflict resolution purpose is met. Note that among the safety concerns, air traffic collision risk is also a very important issue [10]. Collision risk is a numeric measure to assess the safety level of a given airspace together with the corresponding traffic scenario. While CD&R works as a tactical measure to improve traffic safety, collision risk can provide a holistic view towards the traffic within a region and for a given time period. Therefore, collision risk analysis can work as a strategical measure to help to improve traffic safety. It is stipulated by the International Civil Aviation Organization (ICAO) that the collision risk for a nation's airspace should not outstrip a target level of standard (TLS) which is normally set to be 5.0×10^{-9} fatal accident per flight hour (fapfh) [11]. With respect to the ever-increasing traffic demand, the collision risk of the traffic in some countries is reaching the TLS. It is therefore of great significance to reduce the collision risk without compromising the traffic demand.

Collision risk estimation is pertaining to both airspace structure optimization and ATFM. Scientists therefore have proposed several mathematical models for collision risk estimation [12, 13]. Nevertheless, not too many researches on collision risk are available in the literature. The main reason is that those collision risk estimation models are mathematically complicated due to the complex nature of ATSs. Moreover, those models require too much traffic data and aircraft performance data to work out the parameters involved in those models. As a consequence, those models are usually managed by organizations such as ICAO and Federal Aviation Administration (FAA), and they are mainly used for safety assessment purpose. As the civil aviation industry is undertaking a serial of innovations and renovations, many classified documents and data are now declassified and available to the academia and scientific research on collision risk emerged, though still in a small body of quantity as compared to other ATM researches due to its complex nature.

With more flights flying in RVSM airspaces, the probability of loss of separation due to normal height deviations (altimeter system errors) or large height deviations (level burst, wake turbulence, traffic collision avoidance system resolution, coordination failure, etc.) can be very high, which may lead to mid-air collision. In order to reduce vertical collision risk, scientists in the literature have proposed several ways to achieve that goal. In [14], the authors for the first time investigated the impacts of flight events such as climb and turn maneuvers on the vertical collision risk. Interestingly, they discovered that the climb and turn maneuvers, specifically during entering and exiting a sector, contribute significantly to increased collision risk. The work in [15] further observed that descend and turn right maneuvers may increase the collision risk when the flights are in the first half of their flight path. In work [16] the authors explored the airway network structure and its impact on collision risk estimation. Ref. [17] unprecedentedly investigated the possibility of setting optimal lateral offsets for a given airspace based on airway-traffic features to mitigate collision risk. In [10] the authors introduced machine learning techniques to detecte the collision risk hot-spot. That work can help with future airspace design/re-design.

The above mentioned studies on collision risk mitigation either reduce risk through airspace optimization or via ATFM. However, the former takes a long time to be implemented while the latter represented by [15] and [14] only makes use of flight plan data instead of real traffic data. In view of this, in this work we propose a more feasible solution to reduce the vertical collision risk. Specifically, for a given real time traffic data that covers aircraft in a given airspace for a given time period, we propose to control the speed of the aircraft so as to reduce the TVR. To do so, we propose a bi-objective optimization model in which the first objective aims minimize the TVR while the second objective aims to minimize the traffic delay caused by aircraft speed changes. In order to solve the proposed optimization problem, we resort to evolutionary computation techniques and two well-known algorithms named NSGA-II [18] and NSGA-III [19] are introduced and slightly modified to fit for the formulated problem. In order to validate if the proposed research idea is feasible for practical usage, we carry out experiments on sixteen traffic sample datasets that cover the daily traffic in the en-route airspace of the Singapore FIR. Experiments demonstrate that by optimizing the proposed model we can get a set of aircraft speed adjustment solutions to reduce the TVR for the Singapore FIR. Since each solution comes with a certain traffic delay, the aviation managers thus can choose the preferred solutions with respect to specific traffic situations to facilitate tactical or strategical air traffic management.

II. Related Backgrounds

A. Vertical Separation Standard

For the sake of safety concerns, ICAO has specified a minimum vertical separation for flights flying instrument flight rules as 1000 ft below 29000 ft, viz., FL290, and 2000 ft above FL290. However, in order to increase airspace capacity, most countries have implemented the RVSM airspace which covers flight levels from FL290 to FL410, inclusive. An RVSM airspace has a vertical separation of 1000 ft.

B. Technical Vertical Collision Risk

In order to estimate the vertical collision risk, scientists suggest to use a cylinder to represent an aircraft. The TVR is mathematically calculated as follows:

$$\begin{aligned} N_{az} = \; & 2P_z(S_z)P_y(0)\Big\{ n_z(\theta^0)\left(1+\tfrac{|\bar{y}|}{|\bar{x}|}+\tfrac{\lambda_{xy}}{\lambda_z}\tfrac{|\bar{z}|}{|\bar{x}|}\right)+ \\ & n_z(\theta^{180})\left(1+\tfrac{|\bar{y}|}{2V}+\tfrac{\lambda_{xy}}{\lambda_z}\tfrac{|\bar{z}|}{2V}\right)\Big\} + 2P_z(S_z)\times \\ & \sum_{i=1}^{n} n_z(\theta_i)\left(1+\tfrac{|\bar{y}|}{2V}+\tfrac{\lambda_{xy}}{\lambda_z}\tfrac{|\bar{z}|}{2V}\right) \end{aligned} \tag{1}$$

The above equation involves many variables. Table I records the definitions of all the variables. Note that the estimations of those variables rely on real traffic sample data (TSD) and other supplementary data. More details can be found in [11].

C. Evolutionary Multiobjective Optimization

Many engineering problems involve optimization tasks and very often each task requires optimization of multiple objectives. A multiobjective optimization problem (without loss of generality we consider minimization problem) can be represented as follows:

$$\begin{array}{ll} \underset{\boldsymbol{x}}{\arg\min} & F = (f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), ..., f_k(\boldsymbol{x})) \\ s.t. & g_j(\boldsymbol{x}) \le 0, j = 1, 2, ..., q \\ & h_j(\boldsymbol{x}) = 0, j = 1, 2, ..., r \end{array} \tag{2}$$

where $\boldsymbol{x} = (x_1, x_2, ..., x_m)$ is the set of m decision variables and k is the number of objectives. Note that not every optimization problem carries with the constraints of $g_j(\boldsymbol{x})$ and $h_j(\boldsymbol{x})$.

Since in reality decision variable x_i and/or $f_i(\boldsymbol{x})$ could be discrete and objective $f_i(\boldsymbol{x})$ may not carry with any gradient information or even may not have a concrete mathematical form. In this situation, traditional methods cannot solve such kind of optimization problems. As a result, multiobjective

TABLE I
DEFINITIONS OF THE VARIABLES INVOLVED IN THE MATHEMATICAL FORMULA FOR THE CALCULATION OF TVR.

Variable	Definition
N_{az}	The expected number of fapfh, i.e., TVR, due to the loss of vertical separation
S_z	The vertical separation minimum (1000 ft)
$P_z(S_z)$	The probability that aircraft nominally flying on adjacent flight levels are in vertical overlap
$P_y(0)$	The probability that aircraft nominally flying at the same route are in lateral overlap
$\|\bar{y}\|$	The average of the absolute value of the relative cross-track speed between two typical aircraft flying at adjacent flight levels at the same route
$\|\bar{z}\|$	The average of the absolute value of the relative vertical speed between two typical aircraft which have lost vertical separation
$\|\bar{x}\|$	The average of the absolute value of the relative along-track speed between two same direction aircraft flying at adjacent flight levels at the same route
V	The average ground speed of a typical aircraft
λ_{xy}	The average diameter of a typical aircraft with respect to the standing cylinder model
λ_z	The average height of a typical aircraft with respect to the standing cylinder model
$n_z(\theta^0)$	The horizontal overlap frequency of aircraft flying at adjacent flight levels at same direction route
$n_z(\theta^{180})$	The horizontal overlap frequency of aircraft flying at adjacent flight levels at opposite direction route
θ_i	The angle of intersection between two routes
n	Number of possible θ_i for $\theta_i \in (0^{\circ}, 180^{\circ})$
$n_z(\theta_i)$	The horizontal overlap frequency of aircraft flying at adjacent flight levels at intersecting routes with an angle of $\theta_i \in (0^{\circ}, 180^{\circ})$

evolutionary algorithms (MOEAs) emerged and have been broadly applied to solve diverse multiobjective optimization problems [20]. Several state-of-the-art MOEAs are NSGA-III [19] (previous version is NSGA-II [18]), MOEA/D [21], MOPSO [22].

As compared to single objective optimization, the concept of optimality is not directly applicable to multiobjective optimization. For this reason, one of the most important concepts regarding multiobjective optimization is the Pareto dominance. Given two feasible solutions $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$ to Eq. 2, then it is said that $\boldsymbol{x}_1$ dominates $\boldsymbol{x}_2$ if the following condition is satisfied

$$f_i(\boldsymbol{x}_1) \leqq f_i(\boldsymbol{x}_2), \forall i \in [1, k] \tag{3}$$

If there does not exist any solution that dominates $\boldsymbol{x}_1$, then $\boldsymbol{x}_1$ is called a Pareto solution. All the Pareto solutions form the Pareto set and the image of the Pareto solutions in the objective space is called the Pareto front.

III. RESEARCH PROBLEM AND MODELLING

A. Research Problem

This paper aims to reduce the TVR for the flights within a given region and time period. As mentioned earlier, the calculation of N_{az} relies on TSD. Table II presents an example of a simplified TSD.

A TSD mainly carries with the cruise information for the flights within a given airspace and a time period. As can be seen from Table II, the TSD provides the navigation aids (Fix_ in the table) the flights visit and the time they reach them. As reflected in Eq. 1, the TSD mainly contributes to the term $n_z(\theta)$ for $\theta \in [0^{\circ}, 180^{\circ}]$.

In order to reduce the TVR, the most practical and effective way is to do ATFM. More specifically, we can change the flight levels and/or aircraft speed such that the overall value of $n_z(\theta)$ can decrease. However, flight level change involves political issues. In this work we propose to control the speed of the aircraft so as to minimize the TVR. Fig. 1 exhibits a graphical illustration of the investigated research problem.

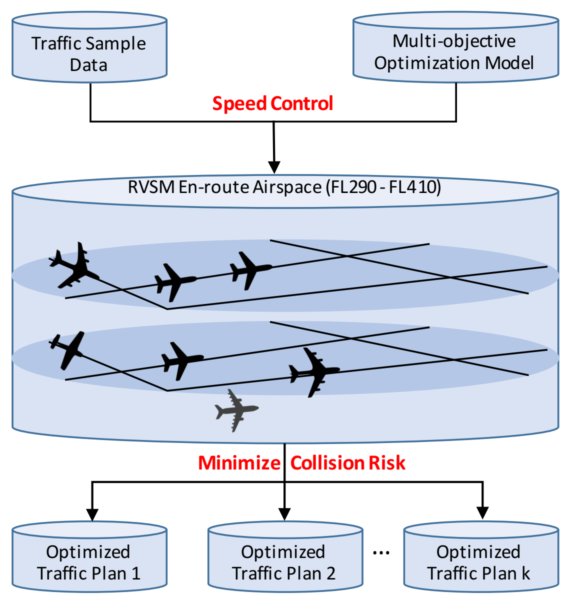


Fig. 1. A graphical illustration of the investigated research problem.

As shown in Fig. 1, for a given TSD we aim to explore the possible speed control solutions for all the flights recorded in the TSD to reduce the TVR. To do so, we propose a multiobjective optimization model and introduce MOEAs to optimize the model. The proposed approach can generate a set of solutions based on which we update the TSD by updating the time the aircraft arrive at each fix. Then we obtain a set of new TSD each of which corresponds to a lower TVR as compared to the original TSD.

B. Research Assumption and Problem Modeling

1) Research Assumptions

TABLE II
AN EXAMPLE OF A SIMPLIFIED TSD WITH 10 FLIGHTS (F1~F10).

Flt	FL	Fix_1	t_1 (UTC)	Fix_2	t_2 (UTC)	Fix_3	t_3 (UTC)	Fix_4	t_4 (UTC)	Fix_5	t_5 (UTC)
F1	390	AKOMA	1/12/18 0:17	VMR	1/12/18 0:23	RAXIM	1/12/18 0:29	OTLON	1/12/18 0:30	VISAT	1/12/18 0:32
F2	360	LATHA	1/12/18 0:19	NIXUP	1/12/18 0:25	ESPOB	1/12/18 0:46	ESBUM	1/12/18 1:05	ELALO	1/12/18 1:10
F3	320	AKOMA	1/12/18 0:20	VMR	1/12/18 0:26	RAXIM	1/12/18 0:33	OTLON	1/12/18 0:33	VISAT	1/12/18 0:36
F4	350	KIMAT	1/12/18 0:25	VPK	1/12/18 0:34	BUVAL	1/12/18 0:37	VEPLI	1/12/18 0:41	NOPAT	1/12/18 0:48
F5	300	ATETI	1/12/18 0:29	NIMIX	1/12/18 0:33	OBGET	1/12/18 0:42	TOMAN	1/12/18 0:49		
F6	360	KIMAT	1/12/18 0:29	VPK	1/12/18 0:40	BUVAL	1/12/18 0:42	VEPLI	1/12/18 0:46	NOPAT	1/12/18 0:52
F7	350	AKOMA	1/12/18 0:29	VMR	1/12/18 0:36	RAXIM	1/12/18 0:43	OTLON	1/12/18 0:44	VISAT	1/12/18 0:47
F8	400	HOSBA	1/12/18 0:32	TOMAN	1/12/18 0:46	VERIN	1/12/18 0:57	LUSMO	1/12/18 1:06	AKMON	1/12/18 1:49
F9	330	KIMAT	1/12/18 0:35	VPK	1/12/18 0:45	IDSEL	1/12/18 0:50	URIGO	1/12/18 0:51	VISAT	1/12/18 0:55
F10	390	AKOMA	1/12/18 0:37	VMR	1/12/18 0:44	RAXIM	1/12/18 0:50	OTLON	1/12/18 0:51		

As illustrated in the above subsection, we aim to change the speed of each aircraft recorded in a given TSD. In order to simplify the research problem, we make the following assumptions.

i) All the flights recorded in the given TSD are level flights, i.e., each flight is flying at a constant flight level. This assumption is in line with real traffic scenario. Flights normally cruise at constant altitudes. In case of abnormal events like convective weather, flights may prefer to adjust speed or detour to avoid the affected region instead of changing altitudes.

ii) Each flight cruises at a constant speed. Since normally each flight will traverse multiple fixes, if we consider the speed for each airway segment to be different, then the scale of the optimization problem would be extremely high as there could be thousands of flights in a TSD. This assumption is made to reduce the scale of the optimization problem.

iii) The ground speed of a typical aircraft ranges from 380 knots to 580 knots with an interval of 10 knots. In the calculation of the TVR, the average ground speed is set to be 460.37 knots based on the one month TSD and the variations of the speed of the aircraft is assumed to follow the truncate double exponential distribution with the lower and upper limits being -100 knots and 100 knots [11]. We set the interval of the speed range to be 10 knots to reduce the scale of the optimization problem.

2) Problem Modelling

For a given TSD, we need to do the data cleaning and get a new TSD. Table III provides the definitions of the necessary variables for formulating the research problem.

TABLE III
DEFINITIONS OF THE NECESSARY VARIABLES FOR MODELLING THE RESEARCH PROBLEM.

Variable	**Definition**
m	Number of flights in the cleaned TSD
a_i	Number of fixes the *i*-th flight needs to traverse
t_i^j	The original time that the *i*-th flight arrives at the *j*-th fix of its path (from TSD)
T_i^j	The adjusted time that the *i*-th flight arrives at the *j*-th fix of its path (updated TSD)
v_i	The ground speed of the *i*-th flight
$\boldsymbol{V}$	A speed vector containing v_i, $\forall i \in [1, m]$
N_{az}^0	TVR based on the original TSD
N_{az}^*	TVR based on the new TSD with respect to speed vector $\boldsymbol{V}$

Based on the variables shown in Table III, we then formulate our research problem as the following bi-objective optimization problem:

$$\begin{cases} f_1 = \arg\min_{\boldsymbol{V}} \; N_{az}^* - N_{az}^0 \\ f_2 = \min \sum_{i=1}^{m} |t_i^{a_i} - T_i^{a_i}| \end{cases} \tag{4}$$

In the above equation, f_1 aims to work out the optimal speed vector $\boldsymbol{V} = \{v_i | \forall i \in [1, m]\}$ to update the information of the flights in a given TSD such that the TVR can be further reduced ($f_1 < 0$). As the speed adjustments to the aircraft will change the time they reach the fixes, then objective f_2 aims to minimize the traffic delay.

IV. RESEARCH METHODOLOGY

A. *Methodology Framework*

In order to solve the proposed bi-objective optimization problem, we introduce two state-of-the-art algorithms, viz., NSGA-II and NSGA-III. For a given TSD and an airspace configuration, we apply the two algorithms to figure out the optimal speed control solutions to reduce the TVR. Fig. 2 illustrates the methodology framework.

Note that both NSGA-II and NSGA-III are population based algorithms. As can be seen from Fig. 2, a MOEA will initialize a population consist of a set of individuals. For a given TSD and an airway network structure, we evaluate the fitness of the individuals in terms of TVR and traffic delay and we then figure out the Pareto solutions. When the termination condition, i.e., the maximum generation, is not met, we update the population based on genetic operations and new individuals are generated. The Pareto solutions will be updated based on the new individuals.

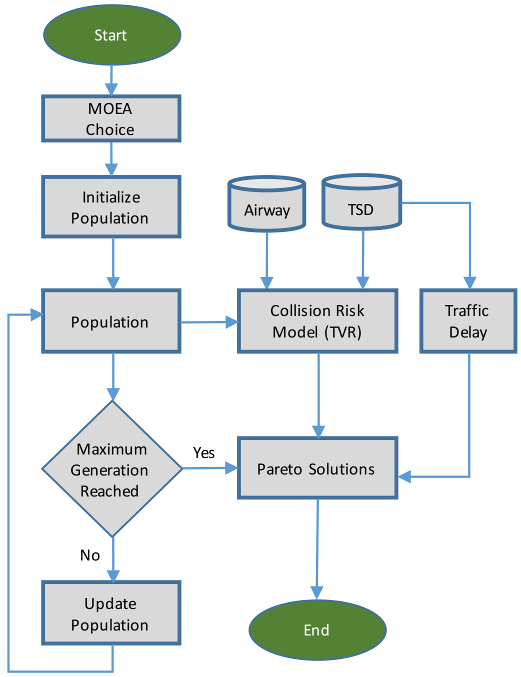


Fig. 2. An overview of the introduced MOEA for reducing TVR with respect to a given TSD and an airspace configuration.

Since there is no guarantee that NSGA-II absolutely outperforms NSGA-III and vice versa, we therefore apply each algorithm to the tested TSD and merge the Pareto solutions obtained by each algorithm and then figure out the final solutions.

B. Individual Encoding and Decoding

As mentioned earlier, we aim to work out the speed sequence $\boldsymbol{V} = \{v_i | \forall i \in [1, m]\}$ for Eq. 4. Based on our assumptions presented in subsection III-B we encode $\boldsymbol{V}$ as an integer sequence with $v_i \in \{380, 390, ..., 580\}$, $\forall i \in [1, m]$.

Note that v_i represents the speed of flight F_i. Let $\mathrm{R}_i = (\mathrm{fix}_i^1, \mathrm{fix}_i^2, ..., \mathrm{fix}_i^{a_i})$ be the route that F_i will traverse with fix_i^j being the j-th fix and T_i^j being the time the flight reaches fix_i^j. Based on $\boldsymbol{V}$ we update the TSD. Specifically, we update T_i^j for all $j \in [1, a_i]$ based on v_i for all $i \in [1, m]$. In the case when fix_i^j is out of the given FIR (this occasionally happens for a given TSD), we still update T_i^j but fix_i^j will not be considered during the calculation of the horizontal overlap frequency, i.e., $n_z(\theta)$.

C. Genetic Operations

Both NSGA-II and NSGA-III use genetic operations which include crossover and mutation to update the population so as to generate new individuals. In this work we apply simple single point crossover and mutation operations.

For a population of individuals, we implement the crossover operation pairewise. Given two individuals $\boldsymbol{V}_1$ and $\boldsymbol{V}_2$, we swap the information of the two individuals starting from a random position $rd \in [1, m]$ with the crossover probability pc and therefore get two new individuals $\boldsymbol{V}_1'$ and $\boldsymbol{V}_2'$. For each of the new individuals we randomly mutate one of its elements, i.e., randomly choose an integer from the range of 380 to 580 at an interval of 10, with the mutation probability pm.

V. Experimental Study

A. Traffic Sample Data

In the experiments, we use the TSD data that records the flights within the Singapore FIR for the time period of December 2018. The one-month TSD contains 44215 flights. After data cleaning we get a new TSD with 33366 flights with the total flying time being 23976 hours. Fig. 3 visualizes a snapshot of the traffic scenario at FL300 within Singapore FIR.

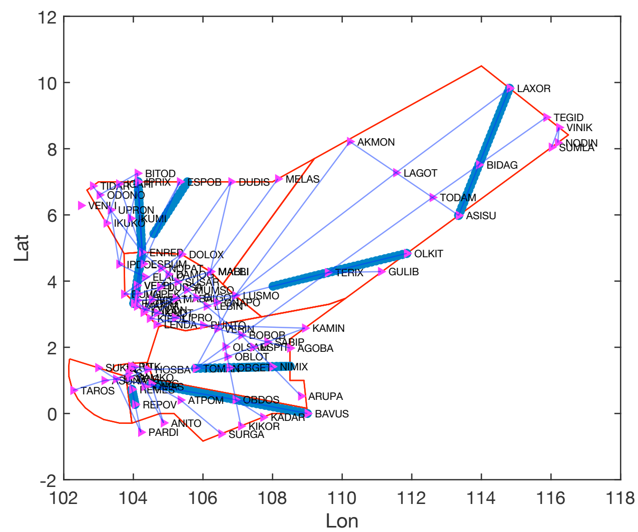


Fig. 3. A snapshot of the traffic scenario with the Singapore FIR.

In Fig. 3 the red curves are the boundaries of the Singapore FIR, while the blue dots are the paths of the flights. Note that the calculation of the TVR is time consuming. For the one-month TSD, it takes about 20 minutes on a personal laptop (CPU: i9, RAM: 32GB) to get the TVR. Since a multiobjective evolutionary algorithm is a population based algorithm, and each population is composed of a set of individuals each of which will correspond to a new TSD for the investigated research problem. In order to save computational time, in the experiments we divide the one-month TSD into daily TSD. We then carry out experiments on sixteen daily TSD, i.e., TSD from Dec 1 to Dec 16.

B. Experimental Settings

In the experiments, some parameters as listed in Table I and the hyper-parameters of the introduced optimization algorithm are fixed as what are shown in Table IV.

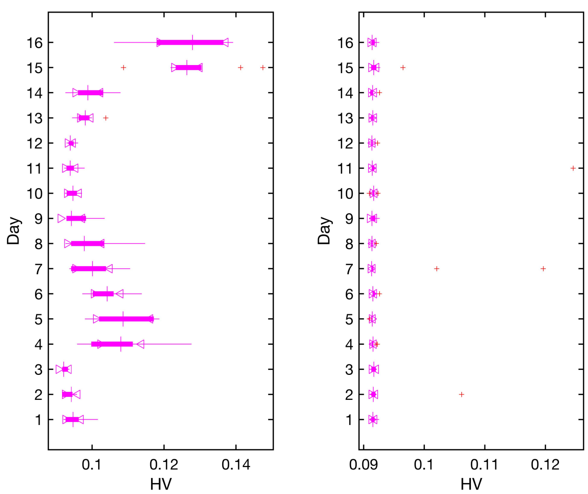
Note that when calculating the TVR, a given TSD mainly affects the values of $n_z(\theta)$. Therefore, we fix the parameters listed in the left column of Table I for all the tested TSD. The settings of the hyper-parameters regarding the introduced optimization algorithm are based on experience. All the experiments are carried out on a server (400 CPUs and 1 TB RAM) at the High Performance Center affiliated with Nanyang Technological University and the implementation environment is Python 3.8.

TABLE IV
SETTINGS OF THE PARAMETERS NEEDED FOR THE CALCULATION OF TVR AND THE HYPER-PARAMETERS OF THE INTRODUCED ALGORITHM.

Parameter	**Value**	**Parameter**	**Value**
$P_z(S_z)$	1.43134e-10	pc	0.8
$P_y(0)$	0.14788	pm	0.2
$\|\bar{y}\|$	20 knots	$psize$	100
$\|\bar{z}\|$	1.5 knots	gen	100
$\|\bar{x}\|$	15 knots	$iter$	20
V	460.37 knots	ns	30
λ_{xy}	0.02605 nm		
λ_z	0.00744 nm		

C. Algorithm Performance Analysis

For each tested TSD, we run each of the introduced two algorithms independently for 20 times. We record the Pareto solutions generated in each run. For multiobjective evolutionary algorithms, the hypervolume is an important metric to evaluate the performance of the algorithms. Fig. 4 demonstrates the boxplots of the hypervolume of the Pareto fronts obtained by the introduced algorithms for 20 independent runs.



(a) NSGA-II (b) NSGA-III

Fig. 4. Boxplots of the hyper-volume of the Pareto fronts obtained by (a) NSGA-II and (b) NSGA-III for 20 independent runs when applied to the 16 tested TSD.

As can be seen from Fig. 4, the distributions of the hypervolume values of the Pareto fronts obtained by NSGA-II are wider than that of NSGA-III. This indicates that the performance of NSGA-III is relatively more stable than that of NSGA-II. By further looking into the Pareto fronts yielded by those two algorithms we notice that NSGA-III generates less solutions than NSGA-II does on most of the tested TSD. As a consequence, it is not sufficient to only rely on solutions generated by a single algorithm with respect to the large scale optimization problem investigated in this work. We therefore work out the final solutions by merging the Pareto solutions obtained by those two algorithms.

Fig. 5 visualizes the final Pareto fronts with respect to each TSD by merging the solutions obtained by NSGA-II and NSGA-III. Since the values of TVR are quite small, in Fig. 5 we visualize the values of 'Equiv' which is the summation of $n_z(\theta)$ as shown in Eq. 1 in order to distinguish the Pareto solutions. But even by doing this, we still can see from Fig. 5 that the Pareto solutions for the eighth and eleventh TSD still look overlapped as the values of 'Equiv' are quite close to each other. We can see from Fig. 5 that for all the TSD except the second and the fourteenth, there exist multiple speed control solutions to reduce the collision risk.

D. Technical Vertical Risk Analysis

The above experiments show that by optimizing the proposed optimization model we can get a set of speed adjustment solutions to a given TSD to improve the TVR. Note that each speed adjustment solution carries with a corresponding cost reflected by the traffic delay as adopted in this work. From the Pareto front corresponding to each TSD, we choose the two corner solutions, i.e., solution 1 (the solution with smallest non-zero delay) and solution 2 (the solution with largest delay), to further analyze their impacts on the TVR.

Table V records the basic properties of the two solutions. We can observe from Table V that solution 1 can help to further reduce the TVR and only cause a very small amount of traffic delay. Although solution 2 can help to reduce the TVR a bit more as compared to solution 1, it comes with relatively larger traffic delays. In real applications, aviation decision makers can choose solution 1 for tactical ATM. They can also choose solution 2 to do strategic management. They even could choose other solutions from the Pareto front, depending on specific traffic scenarios and considerations.

Note that the percentage of the improvement on the TVR as reflected in Table V is not that significant. Also, the Pareto solutions to each TSD as can be seen from Fig. 5 are not too many. Actually, the above results are reasonable and promising. For one thing, the optimization problem to be solved is a large-scale concave optimization problem. No algorithm can find the global optimal solutions within polynomial time. For another thing, many feasible solutions have been dominated by the corner solution with zero delay during the evolution process of the algorithms and the resultant Pareto solutions are therefore small in numbers. The main reason for the small number of Pareto solutions is that the experiments are carried out on real-world traffic data. The traffic has been well planned by aviation navigation service providers and managed by the controllers to reduce mid-air aircraft collisions. Therefore, the efforts to further reduce the collision risk are limited, and this is the reason why the percentage of risk improvement is low as the TVR for the Singapore FIR is already below the TLS.

E. Discussion

The above experiments demonstrate that the proposed optimization model can help to reduce the TVR through aircraft speed control. The introduced optimization algorithms can solve the proposed model well, although the Pareto solutions obtained by the algorithms may not be the global optima due to the complex nature of the optimization problem.

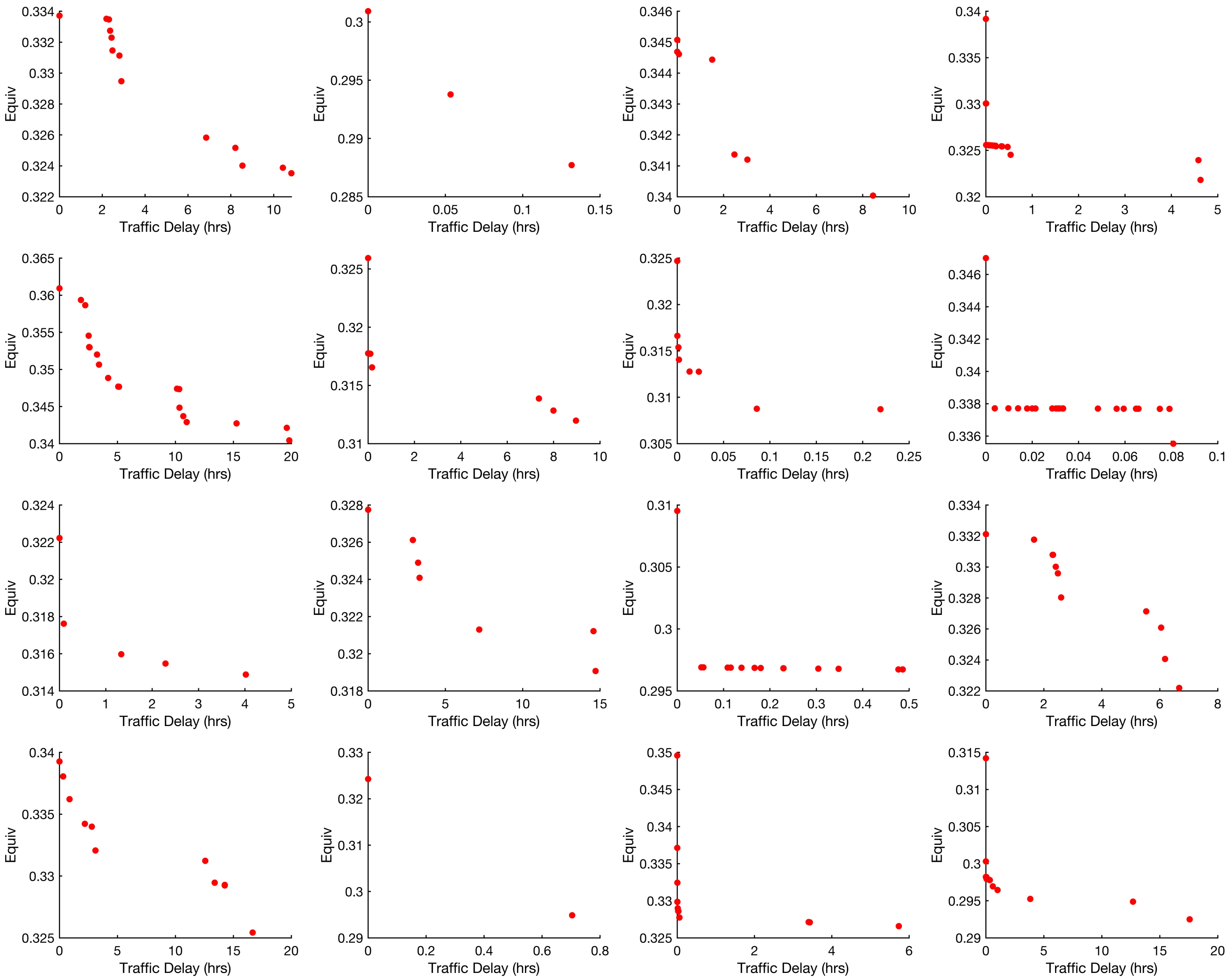


Fig. 5. Visualization of the Pareto fronts obtained by merging the solutions obtained by the introduced multiobjective optimization algorithms for 10 independent runs when applied to the 16 tested TSD.

It should be pointed out that the research problem is solved under certain assumptions. However, the research idea is feasible for real applications. For real applications, we need to modify the assumptions made in this work. For example, we need to remove the first assumption in which we assume that all the flights are level flights. In this case, we need to consider the total vertical risk instead of the TVR. We also need to release the second assumption to let the speed of the aircraft vary when traversing different airway segments and the interval for the speed range can be changed. Moreover, extra constraints can be added to the proposed optimization problem to make it fit for practical implementations.

Note that the problem of minimizing collision risk is definitely a concave optimization problem and could involve multiple objectives. We are positive that evolutionary computation techniques will work as a potent tool for solving not only the collision risk minimization problem, but also other kinds of air traffic issues.

VI. Conclusion

The year on year increase of air traffic demand poses severe challenges to modern air traffic management. How to ensure the traffic safety without compromising the demand is quite challenging. Collision risk estimation can provide a holistic view of the traffic safety level. In this work we proposed a multiobjective optimization based model to minimize the TVR of air traffic via aircraft speed control. To solve the proposed model, we introduced two well-known multiobjective evolutionary algorithms named NSGA-II and NSGA-III. We approximated the optimal solutions to the proposed model by merging the Pareto solutions obtained by NSGA-II and NSGA-III. To validate the effectiveness of the investigated research problem, we carried out experiments on sixteen daily traffic sample datasets that cover flights within the Singapore FIR for December 2018. Experiments indicated that by solving the proposed model, a set of speed adjustment solutions each of which carries with a resultant traffic delay can help to further reduce the TVR.

TABLE V
THE IMPACTS OF THE TWO CORNER SOLUTIONS CORRESPONDING TO EACH TSD ON THE TVR.

Day	N_{az}^0 (fapfh)	Solution 1			Solution 2		
		N_{az}^* (fapfh)	f_2 (hrs)	$\frac{100*(N_{az}^*-N_{az}^0)}{N_{az}^0}$	N_{az}^* (fapfh)	f_2 (hrs)	$\frac{100*(N_{az}^*-N_{az}^0)}{N_{az}^0}$
1	1.46518e-11	1.46428e-11	2.1928	-0.0617	1.42042e-11	10.8233	-3.0552
2	1.32707e-11	1.28984e-11	0.0533	-2.8056	1.26323e-11	0.1317	-4.8111
3	1.51504e-11	1.51335e-11	0.0033	-0.1113	1.49293e-11	8.4417	-1.4595
4	1.48912e-11	1.44910e-11	0.0019	-2.6874	1.41296e-11	4.6292	-5.1142
5	1.58468e-11	1.57777e-11	1.8525	-0.4363	1.49471e-11	19.8211	-5.678
6	1.43100e-11	1.39510e-11	0.0022	-2.5086	1.36972e-11	8.9617	-4.2819
7	1.42558e-11	1.39013e-11	0.0003	-2.4869	1.35539e-11	0.2192	-4.9238
8	1.52353e-11	1.48274e-11	0.0039	-2.6771	1.47314e-11	0.0808	-3.3072
9	1.41474e-11	1.39451e-11	0.0944	-1.4302	1.38249e-11	4.02	-2.2793
10	1.43898e-11	1.43182e-11	2.8981	-0.4975	1.40087e-11	14.7122	-2.6479
11	1.35900e-11	1.30354e-11	0.0519	-4.0805	1.30281e-11	0.4861	-4.1346
12	1.45817e-11	1.45663e-11	1.6653	-0.1055	1.41459e-11	6.6706	-2.9886
13	1.48954e-11	1.48426e-11	0.3256	-0.3547	1.42882e-11	16.6614	-4.0765
14	1.42360e-11	1.29467e-11	0.7042	-9.0565	1.29467e-11	0.7042	-9.0565
15	1.53488e-11	1.48015e-11	0.0006	-3.5658	1.43383e-11	5.7328	-6.5831
16	1.37955e-11	1.31854e-11	0.0003	-4.4222	1.28420e-11	17.5722	-6.9118

ACKNOWLEDGMENT

This research is supported by the National Research Foundation, Singapore, and the Civil Aviation Authority of Singapore, under the Aviation Transformation Programme. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of National Research Foundation, Singapore and the Civil Aviation Authority of Singapore.

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