Journal of Industrial Information Integration 52 (2026) 101146

Contents lists available at ScienceDirect

Journal of Industrial Information Integration

journal homepage: www.sciencedirect.com/journal/journal-of-industrial-information-integration

Full Length Article

Investigating the transdisciplinary nature of Air Traffic Management (ATM) networks

Richard Curran [a], Yalin Li [a,*], Xiaojia Zhao [b]

[a] Aviation Management, Department of Engineering, Tait Building, City St George's, University of London Northampton Square, London EC1V 0HB, UK

[b] College of Aerospace Engineering, Nanjing University of Aeronautics and Astronautics. Yudao street No. 29, Qinhuai District, Nanjing City, Jiangsu Province 210016, PR China

ARTICLE INFO

Keywords:
Air traffic management (ATM) networks
Air transport
Multi-criteria decision making
Robustness
Resilience
Transdisciplinary engineering

ABSTRACT

The associated research work to be presented will address issues of modelling efficiency and therefore develop insights into the nature and principles of how ATM networks are constructed and how they can be more effectively designed, by using the operational performance nature that becomes evident through the modelling. In general, the paper will present how the simulation tool a) models the network, b) implements the optimisation technic, and c) validates the approach. Consequently, this provides the platform that is then used for two real ATM networks, in both China and Europe as two selected case studies, in order to provide results. At a more fundamental abstract level, such a network is a complex system, or system-of-systems that is transdisciplinary in nature. The inherent design parameters (1) are different and diverse in nature, including aircraft, airports, and routes; the operational parameters and variables (2) are multicriteria in nature, and diverse in units and type; and causes-of-change (3) are disruptive at a mono, inter, and trans-disciplinary levels to effect multi-attribute characteristics and performance metrics that attempt to capture the impact on the network system functioning as designed and planned, which are integrated in a systematic network simulation application Consequently, the authors intend to use the application related to ATM network performance in order to understand at a more fundamental level elements of transdisciplinary science and transdisciplinary performance both in terms of optimal level (capacity) and robustness (performance reduction and recovery).

1. Introduction

This paper presents an Air Traffic Management (ATM) simulation tool [1] developed under the paradigm of Industrial Information Integration (III) [2,3], which a) models a representative ATM network [4,5], b) implements a simulation technique that aims to improve the understanding and performance of the network [6–8], and c) validates the approach by investigating the ability to capture the transdisciplinary nature [9,10] of the network and its response to system-level interactions and interventions through integrated information analysis. As a practical application platform of III, the network simulation provides a platform that is applied to a realistic Chinese ATM network, generating realistic results and conducting fundamentally transdisciplinary analysis by unifying multi-source operational data and cross-domain industrial information. This simulation tool innovatively integrates transdisciplinary models and the III paradigm, supporting multi-objective outputs that are hard to be achieved by analogous aviation tools.

At a more fundamental level and an ATM network is a complex industrial system, or System-of-Systems (SoS) that is highly transdisciplinary in nature. The inherent design parameters (1) are heterogeneous in nature, including aircraft, airports, and the ATM routes and are digitally mapped through III's physical resource integration; the operational parameters and variables (2) are multidimensional and multicriteria in nature (and diverse in units and type, which are standardized via III's data integration mechanism; and the causes of change); (3) are disruptive at a mono, inter, and transdisciplinary level to effect multi-attribute characteristics and performance metrics that attempt to capture the impact on the network system functioning as designed and planned. Consequently, this transdisciplinary nature will be reviewed in the light of current theories and principles of Transdisciplinary Engineering, with III acting as the technical carrier for the verification of such theories addressing robustness

* Corresponding author at: Aviation Management, Department of Engineering, Tait Building, City St George's, University of London Northampton Square, London EC1V 0HB, UK.

E-mail address: Yalin.Li.3@citystgeorges.ac.uk (Y. Li).

https://doi.org/10.1016/j.jii.2026.101146

Available online 1 June 2026

and resilience.

2. Network information integration

2.1. Network components

Fig. 1 presents a simple example of an ATM network and its adaptation for simulation. Firstly, the solid lines and nodes demonstrate the connectivity of an ATM network, whether established or evolving. Nodes represent airports and waypoints (interim connecting points). They have the function of generating and receiving traffic flow and transferring traffic flow. Segments are used to describe an 'air route', which links nodes together to form the network's connectivity. The flight movements will transfer 'through' these segments (shown by the red arrows in Fig. 1b). These modelling characteristics collectively form the fundamental components that construct an ATM network simulation to model the system dynamics and inherent transdisciplinary nature of such a complex system with design and operational elements given by the airline, airport and ATM infrastructures, their software and hardware technology platforms, and the air transportation providers that provide operational service to the passenger customers and wider business, community and indeed economies associated with them [4–7].

There are capacity units that are distributed to all the sectors in the network and so Fig. 1b highlights one flight moving from one sector S1 to another sector S2. The sectors are mapped by the sector nodes and sector borders. When a flight crosses the sector border between S1 and S2, the capacity units in S1 will have one more unit available, while S2 will have one less.

Another constraint to consider is the capacity of the airport which will have limitations in generating and receiving flights while sinks do not and have unlimited capacity due to the fact that they are not participating in the operation of the network but help generate it. Here the capacity unit is defined as a unit that quantifies the ability of the nodes or sectors when they are operating the flights in the network. One capacity unit in one node or sector suggests that the node or sector is able to operate one flight for a particular time step. Since the simulation of the capacity unit is not the main objective of this study, the capacity unit model is adapted from empirical data and other works [10,11]. There are various factors that have an impact on the capacity of the nodes or sectors, but in order to simplify the model, the capacity distribution only uses the quantification of capacity units to demonstrate this performance and test that the capacity units are equally distributed to the nodes or sectors.

2.2. Flight components

Table 1 presents the information parameters that characterize any instance of a flight, for example, relative to a particular flight's Airport's *Origin* 'O' and *Destination 'D'*. The aircraft traffic flow in Fig. 2(red path) that equates to flights in an ATM network inherits this formalized flight information (as described in Table 1). Fig. 1a also shows how a flight travels from its origin to destination when considering the movement from 'circle to circle' or airport to airport. As Fig. 2 shows, the flight will have its OD (Origin and Destination) pairing, STD (Scheduled Time of Departure), STA (Scheduled Time of Arrival), ATD (Actual Time of Departure), ATA (Actual Time of Arrival) and CAC (Code of Aircraft). Subsequent to a flight being generated, the model also generates the associated flight path, shown as the segments with arrows in Fig. 1a, where a flight path is a sequence of air routes that the aircraft will fly. The routing algorithm used to generate the flight path in the simulation is the Floyd-Warshall shortest path strategy [10]. To meet different requirements of the simulation, the flight generation process is varied; for simple tests, the flight is randomly generated by a demand data roulette (highlighted subsequently through Fig. 3), while the specific case study of the Chinese market presented herein uses generated fixed-schedule and true-schedule forms of real air traffic. Additionally, after obtaining the flight path, the distance to the destination can be calculated and all flights have a "distance" feature to locate them as they change according to time; also, the flight may be cancelled or detour in case of disruption.

Table 1
Flight features.

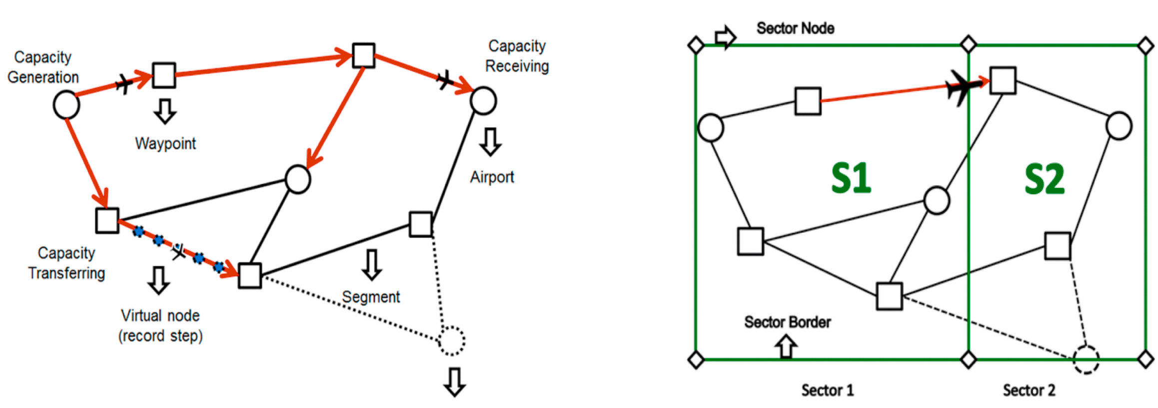
Category	Term	Notation
Airport	Origin	O
	Destination	D
Time	Scheduled Time of Departure	STD
	Scheduled Time of Arrival	STA
	Actual Time of Departure	ATD
	Actual Time of Arrival	ATA
Aircraft	Code of Aircraft	CAC
Path	Flight Path	FP(O, W...W, D)
Distance	Distance	Dis
Cancel	Cancel	CT(ure)/CF(alse)
Detour	Detour	DT(ure)/DF(alse)

2.3. Flying rules

The flying rules in the network determine how the simulation represents the flight operations in the ATM network using a number of guiding rules.

2.3.1. Generation rules

Based on the flight demand, the flights in the network will be generated according to a roulette of each OD (Origin and Destination)



a) b)

Fig. 1. a) Network model and b) Sector capacity model.

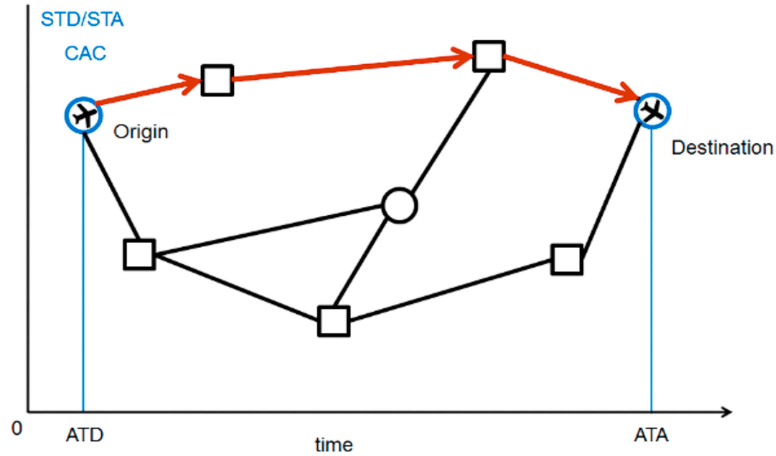


Fig. 2. Flight components.

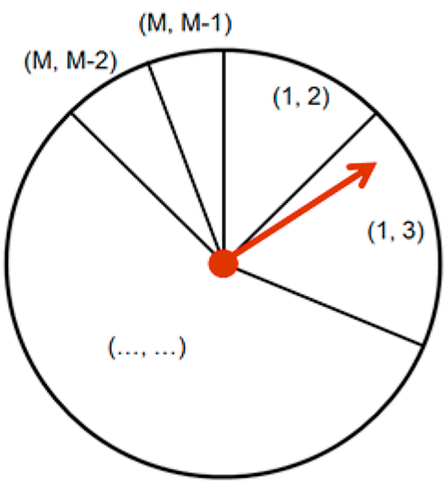


Fig. 3. Random roulette.

pairing (shown in Fig. 3). In Fig. 3, each OD pair has a proportion of the demand from this OD pair to the demand of the entire network. Here, the simulator generates a random number and uses the roulette to determine the OD pair for the flights. As highlighted in Fig. 1, each flight must take off from one airport and land in another Airport. After determining the OD of a flight, its flight path can be generated, where the basic routing strategy is to assume the shortest path strategy, using the aforementioned Floyd-Warshall algorithm [10]. The algorithm is able to generate all of the shortest paths between all OD pairings and therefore, the scheduled flight time can be derived by calculating the air route length from the combined flight path segments.

2.3.2. Forwarding rules

The network operation will in principle follow the first-come, first-served rule. However, in certain situations there could be more flights reaching a waypoint at the same time. The forwarding will be according to the ATD of the flight. In Fig. 4, one flight *Flight 1*(blue) would take off at time *t1* and have OD pair (*O1, D1*), and *Flight 2*(purple) will take off at *t2* and have the OD pair (*O2, D2*), while *Flight 3*(green) will take off at *t3* and have the OD pair (*O3, D3*), where $t1 < t2 < t3$. *Flight 3* will 'be approaching' a waypoint and if the capacity at this waypoint (*CW*) is larger than 1, at the next time step, e.g. *t7, Flight 3* will pass through it. However, if the waypoint does not allow the flight to pass, *Flight 2* may want to cross the waypoint at the same time and the waypoint capacity (*CW*) is not sufficient due to *Flight 1* passing through, the last generated flights *Flight 2 and 3* will have to wait or change flight path.

2.3.3. Crisis rules

Disruptions will occur in any ATM network and it is highly meaningful to model such emergent behavior using the simulation presented here. Essentially, such a transdisciplinary model can be used to generate the emergent behavior of complex systems as this can be very disruptive and influential to the robustness and resilience of a system as it recovers from disruptions. If a disruption occurs at an airport, then arriving flights will choose the nearest airport to land at in order to resolve their flight allocation dilemma, as airport capacity utilization is considered in the simulation. Similarly, if a disruption occurs at a waypoint, then a new pathway or flight route will be calculated according to the shortest path rule to accommodate the rerouting to the new destination.

In the real world, canceling flights or changing flight destinations is not simple to model; the ATM, airport and airline Companies must reach an agreement. Furthermore, there is no clear standard for flight cancellation or destination changes. We can always see flights delayed for >10 h without being canceled. However, this simulation tool only simulates one full operational day, covering 24 h plus an additional 6 h for simulator warm-up time.

To simplify the model, a cancellation standard (CCST) and a destination change standard (CHST) are defined. Since weather is unpredictable, flights will only have real-time weather information during the simulation. If a disruption occurs, flights will not know when it will end. Fig. 5 illustrates cancelled flights and flights with changed destinations. For a newly generated flight, if the origin is blocked, the flight will wait until the area reopens and these flights will be waiting in a queue. When the area reopens, the origin area will dispatch new flights first. If there are still capacity units, the waiting flights will depart. Next, those flights that are delayed exceeding the CCST (min) will be canceled. In this simulator, considering the simulation time of traffic is one day, CCST is shorter than real-life scenarios, therefore 180 min is used to facilitate programming. Flights that fail to land fall into two scenarios: one is that the destination is blocked; the other is that the destination does not have enough capacity. Those flights encountering destination blockages will be rerouted directly to another airport, and those lacking sufficient capacity will calculate their estimated arrival time. If the delay is greater than the CHST (min), such flights will be rerouted to another airport. According to CAAC, the waiting time is a maximum 40 min [12].

3. Network evaluation and optimization

3.1. Evaluation simulation process

In Fig. 6, the overview of the simulator functioning is illustrated. To

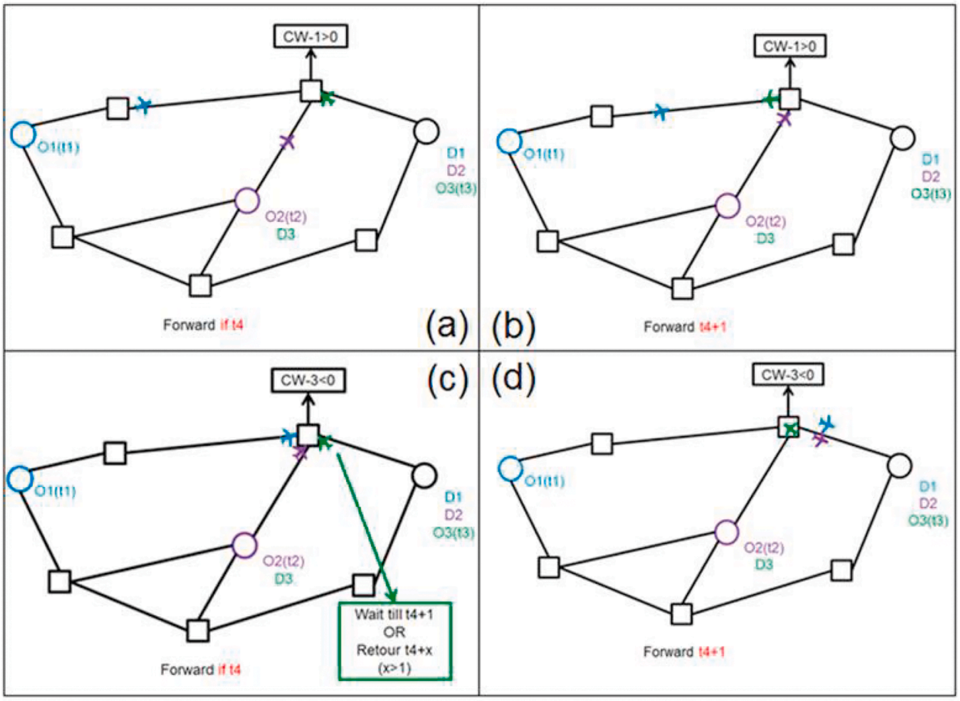


Fig. 4. Flights forwarding.

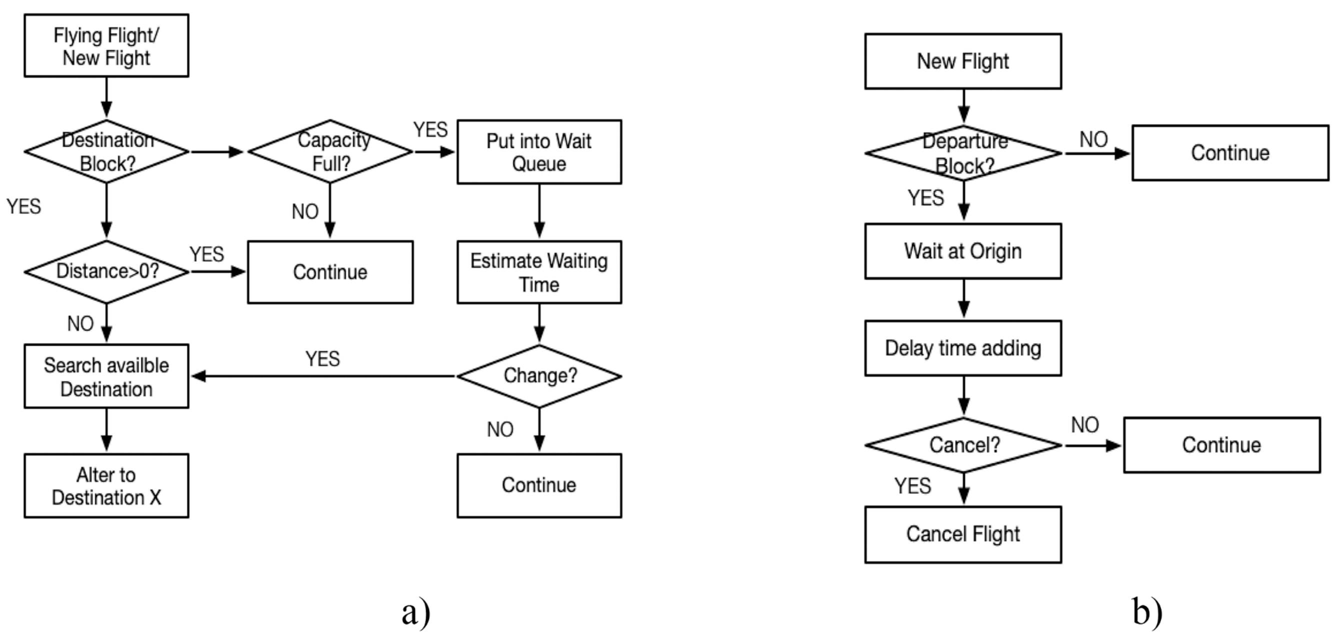


Fig. 5. Judgment process of a) Cancelling and b) Changing flight.

meet various requirements, the information can be related to synthetic networks and artificial networks, or real mirrored models that are very difficult to define and represent properly in models due to their inherent complexity and the challenge of modelling the manner factors that may or may not be influential (and at a similar level of fidelity). There are two ways to generate networks, where for synthetic networks, the real schedule information will be used as profile so that a fixed schedule of flights can be generated to keep the simulator close to reality, while for artificial networks, the flights are only used for demonstration. Therefore, a partial random generation method can be used for the network generation and the flights that fly in the network. It can also generate the required traffic flow, with the operation of the flights being recorded and used for analysis of the system behavior relative to improvements or robustness, which the authors define as a function of performance loss, and resilience, being a function of the time-based recovery from the loss of performance due to a disruptive event [13].

3.2. Optimization simulation process

3.2.1. Optimization algorithm

The simulation tool is based on Simulation Annealing Algorithm (see Fig. 7) [14]. As the results from SA could drop into a local optimal, there

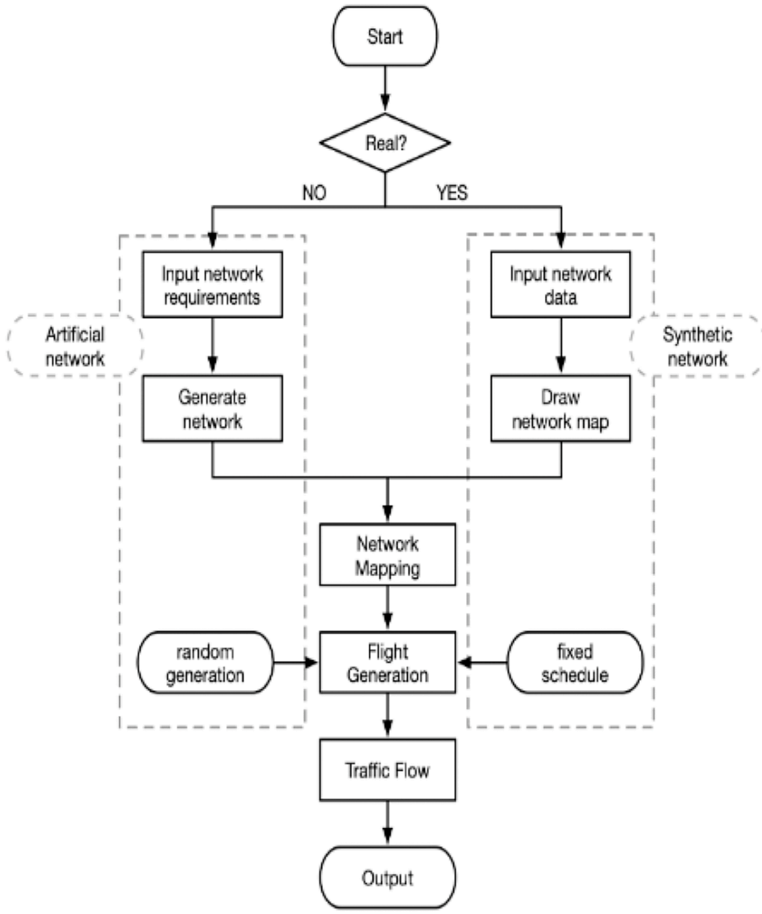


Fig. 6. Overview of the simulator steps in network.

is Metropolis algorithm, which helps to judge if a worse solution will be accepted. For the temperature schedule, as it is to control the simulation process, a stopping criterion is needed, which is the $T_{\min}$ in the cooling process.

$$T(t) = \frac{T_0}{\lg(1+t)} \tag{3.1}$$

In this thesis, the metrics are noted as: tp_0 for the starting temperature, $tp_{\min}$ for the minimum temperature, which is the stopping criteria. The temperature of iteration i is tp_i. Then we can have the temperature schedule:

$$tp_{i+1} = tp_i / \left(1 + i^{\Delta obj_i}\right). \tag{3.2}$$

Δobj_i is the difference between the objective value and the optimal objective value until i iteration.

In the real networks, tp_0 is the same value, and $tp_{\min}$ is used to end the iteration. Therefore, Δobj_i in the simulating process could result into different numbers of iterations of the optimization in different networks. It is easy to see that if the absolute value of Δobj_i is smaller, the temperature will be slowly reduced. This means smaller difference between iterations will result into more iterations to finish the SA process.

The Metropolis rule for the acceptance of the worst solution, the probability $P(\Delta E)$ is used.

$$P(\Delta E) = \exp\left(-\Delta E / k_B T\right) \tag{3.3}$$

Temperature (see Fig. 8), which is a parameter to control the iteration times, is reducing gradually, and when reaching the terminal condition, i.e. the minimum temperature, the SA process will stop. Choosing different starting temperature and minimum temperature, the number of iterations can be controlled. In this case, after 6 iterations, the process reached an end, and the entire simulation cost 45 s.

The converging process is clear in Fig. 8. The vertical axis is the objective that normalized. The blue line is the results of Obj for the current iteration and the red line is for the saved optimal Obj from the start to the current iteration. It can be seen that the simulator can obtain better results gradually and has the ability to jump from poor solution areas and go back to an optimal solution area in 23 iterations, as the temperature schedule controlled it.

3.2.2. *Optimization objectives*

The objective functions in the simulation are performance of the air traffic network. The number of flights that successfully arrived and the delay that the flights have are main objectives. For the convenience of simulation and demonstration, the objective functions will be normalized. Thus, the results from the simulation will be in the range of (0,1]. To find a relative better solution from the optimization process, the two objectives will be weighted and combine into one objective. In this model, the performances of network can be defined as objectives for evaluating. Objective 1 (Obj_1) is

$$EC = FlightSum / FlightScheduled \tag{3.4}$$

where *FlightArrived* is the total number of flights that have been operated in the network, and *Flight Scheduled* is the total number of fights that have been allocated to the network and should be landed; Objective 2 (Obj_2) is a function of network delay,

$$QN = \sum_{t=0}^{T} \left(1 - Delay(t) / Delay_{MAX}\right). \tag{3.5}$$

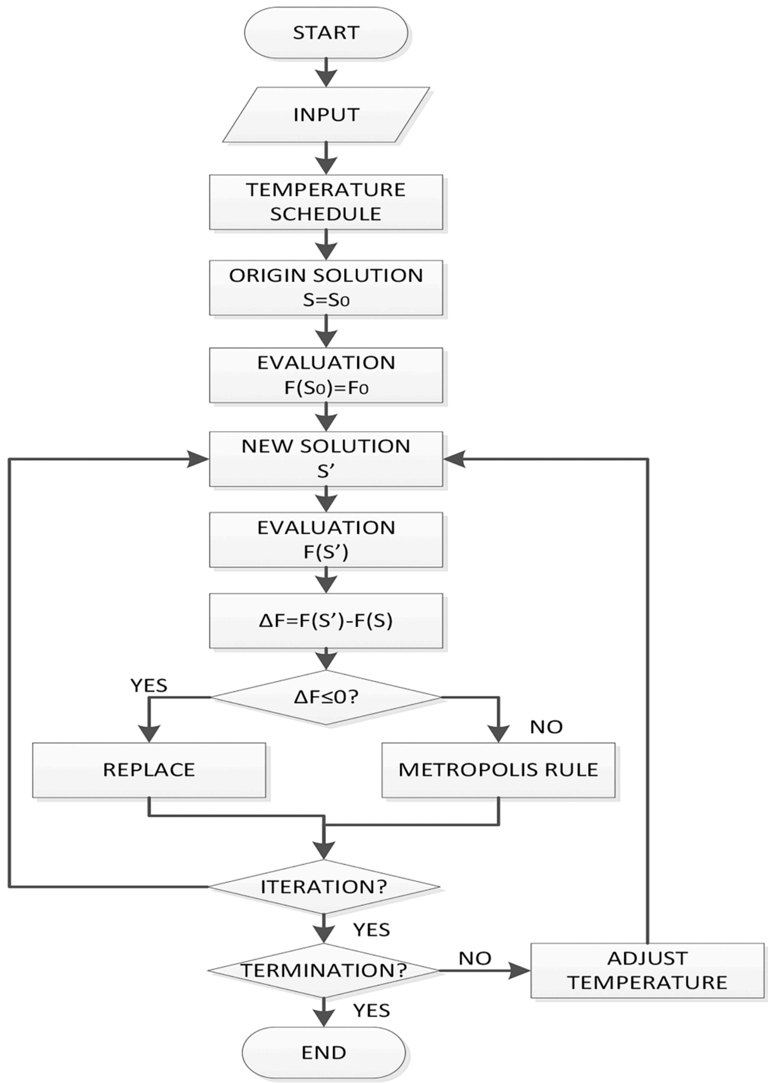


Fig. 7. SA process.

where *Delay(t)* is the average delay of flight departure at time *t*, and $Delay_{MAX}$ is the maximum delay that one flight can have; Objective 1 (*Obj1*) and Objective 2 (*Obj2*) are used to show multi-objective performance of the model and both would be the larger the better. (w_1, w_2) is used for the different weight combinations of the two objectives. Therefore, the objective has

$$Obj_{Multi} = w_1 \times Obj_1 + w_2 \times Obj_2, where w_1 + w_2 = 1. \tag{3.6}$$

3.3. Networks

The process for generating the network shown in Fig. 1a) provides the framework for the simulation process (see Fig. 6) to then operationalize the intent and function of the network using the random roulette algorithm method (see Fig. 3) to populate the simulation for scenario generation. For the Chinese network presented here this is actually a sort of synthetic network in that the network provides verification results for a realistic simulated reality at a given scale of an ATM network. This is a very important point as it is so difficult to capture the behavior of a highly complex network as the measurement and data are not available or at best only at a generalized level. This behavioral analysis is the goal of the ATM network analysis presented and can be used relative to an ATM network design that is an evolution of the addition of airports that can be adapted and evolved to improve capacity, robustness and resilience.

The Chinese ATM network is shown in terms of sectors in Fig. 9a, so this 'synthetic Chinese network' is made up of the actual 150 airports that are taken from the real network (see Fig. 9b). As China is a very large country, there are a lot of national flights that need to be accommodated relative to the ratio that is normal in Europe for international flights, and many of the airports are not international and only 51 airports out of the 150 airports have international flights. According to the traffic demand, those 150 airports can also be managed in various ways and in order to accommodate the huge capacity differences, from 10–2000 flight operations per day, historical traffic data is used to categorize the airports into 3 categories, noted as CATE1, CATE2 and CATE3. CATE1 represent the 10 busiest airports in China, such as Beijing Capital International Airport (ZBAA), while there are 27 airports in CATE2, and further 113 smaller airports in CATE3. There are 953 waypoints in the synthetic Chinese network and four sinks are used to simulate the four global directions that represent the international airports that are connected within the network. This results in 1722 air tracks or flight paths shown in the network plot in Fig. 9b.

A smaller scaled network (see Fig. 9c) can of course also be used to improve computing time and enhance the usability of the simulation capability to run scenarios. In the results presented subsequently, Network T (see Table 2) has 23 airports, with 6 international airports that can generate international flights, and according to the traffic

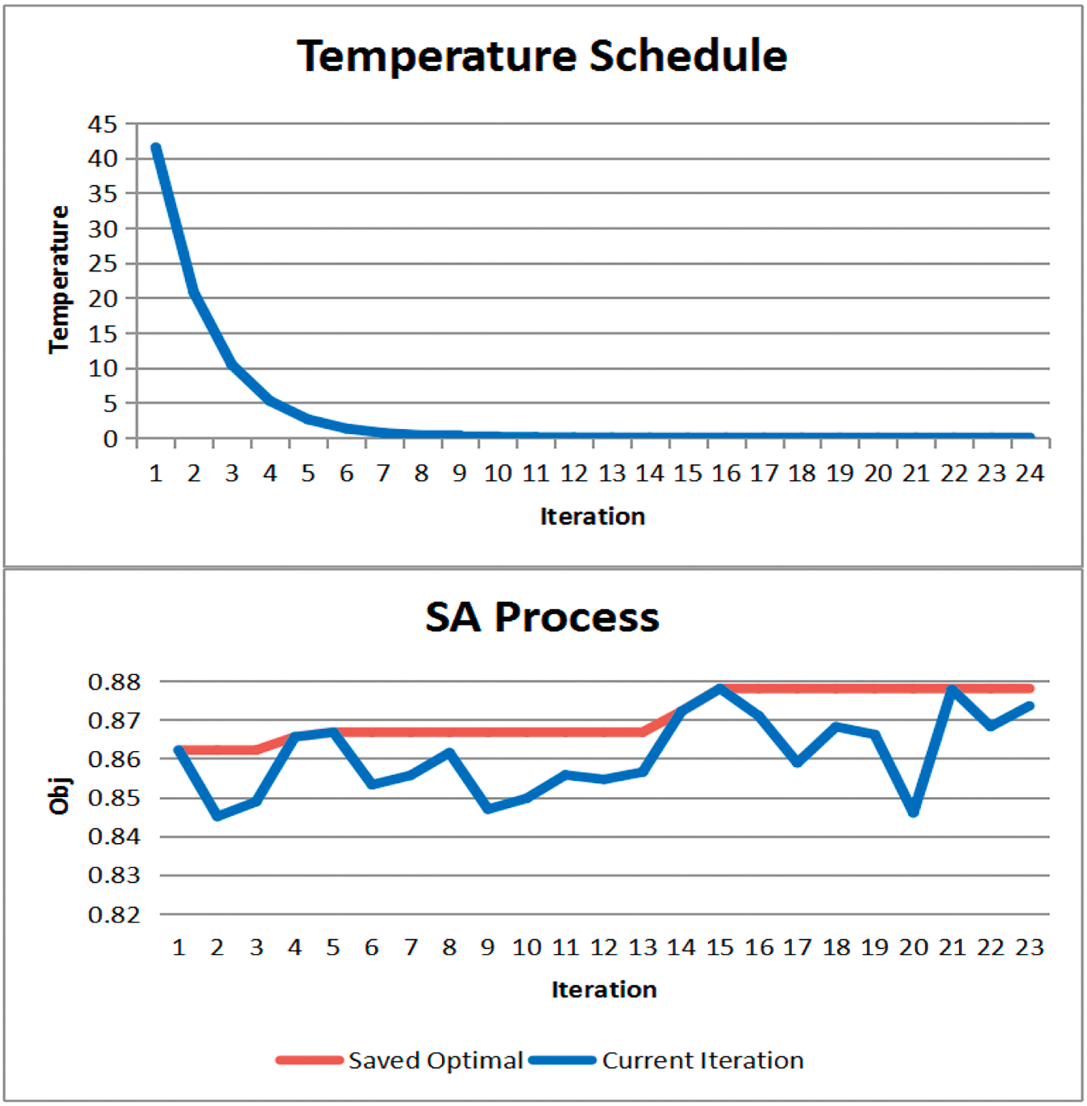


Fig. 8. Temperature schedule of SA process (up) in test network and the converging process (down).

a) b) c)

Fig. 9. The Chinese geographical network and associated ATM network simulation flights.

demand, 23 airports have 1 CATE1 airport, 5 CATE2 airports, and 17 CATE3 airports. The scaled-down network, Network T, has 150 waypoints and 280 air tracks that connect all the nodes together, with 18 sector nodes and 21 sector borders that divide the synthetic Chinese network into 5 sectors. All properties of the networks used in the work are summarized in Table 2.

Table 2
Network characteristics.

Features		Synthetic Chinese Network	Synthetic Chinese Network.t (Network T)
Airports	CATE1	10	1
	CATE2	27	5
	CATE3	113	17
	International	51	6
Waypoints		953	150
Sinks		4	4
Air tracks		1722	280
Sectors		29	5
Sector nodes		93	18
Sector border		120	21

4. Verification

The network simulation provides the platform that is applied to a realistic Chinese ATM network, in providing realistic results and performing analysis that is fundamentally transdisciplinary in nature. This simulation process could provide a guided reference for newly planned networks and, of course, improve existing ones.

4.1. Programming verification

4.1.1. Simulation stability using random number

In Fig. 10, there are three independent simulation results showing the traffic flow changes along with the time step using different seeds. The x-axis is the simulation time and the y-axis is the normalized performance of the network. Seed for generating flights is the only difference in these three simulation processes. For a non-selected seed simulation, the program does not select a specific seed for the random number generation. For selected seed, the seed is manually selected. For a time seed, the seed is dependent on the system time, which means it will change along with the calculation time. Overall they are showing very similar results. This indicates that the simulator is very stable with different seeds and can always give stable results.

4.1.2. Different network scenarios

There are 4 features of a disruption, location, start time, length and the loss of capacity. To test the stability, 5 tests (Sta.Test in Table 3) are selected: Test 1 is for no disruption, and Test 2 to Test 5 have different characteristics of disruption, and the simulator selects these characteristics of disruption randomly. For example, Sta.Test 2 is a disruption that occurs in Sector 2, starts at midnight, lasts for 3 h and is associated with a loss of 20% capacity. The simulator runs each stability test 30 times and the results of each test are based on the same network but different seeds. In Table 3, the deviations of the 30 runs of each test are listed. Obj1 and Obj2 are the objectives of the simulation. They are normalized and represent the delay of the network and the flights served compared with the schedule. For Obj1, the deviations are mostly <0.01, and, for Obj2, the deviations are <0.02. This verifies that the simulator can always give stable results.

Table 3
Different scenarios and deviation of objectives.

Sta. Test	Location	Start	Length	Capacity loss	Deviation of Obj1	Deviation of Obj2
1	NA	NA	NA	NA	0.00048	0.01559
2	2	0	3	20%	0.00822	0.00349
3	4	1	2	20%	0.01047	0.01800
4	4	6	3	50%	0.00773	0.01614
5	3	15	3	20%	0.00980	0.01471

4.2. Network verification

4.2.1. Traffic phase transition

According to the relationship between capacity and delay, capacity can be divided into actual capacity (also known as operating capacity) and maximum capacity (also known as the saturation capacity or capacity limit). (see Fig. 11) [15].

In the synthetic Chinese network, we define the transition capacity of every waypoint as Cw=8, and assume that the capacity at every airport is Ca=1 to simplify the network. The generation rate of the network is λM (flight/time step, M is the number of airports), which corresponds to 20, 66 and 80. Then, the flights number (y-axis) in the network will change as time goes by. (see Fig. 12)

When $\lambda M \leq 66$, the flights number will reach a limit and stabilize, and this means the network is fully functional and there is no congestion. But when$\lambda M > 66$, flights start to accumulate and this trend won't stop, which means the network is congested. Then 66 is the phase transition

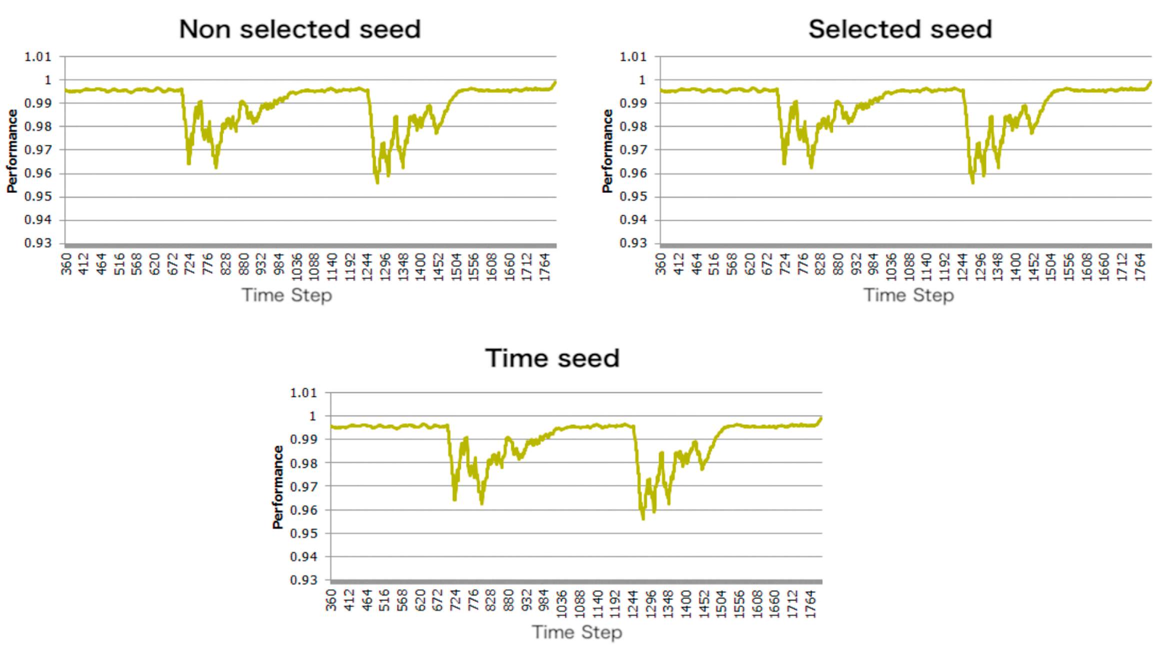


Fig. 10. Results with different seed for random number.

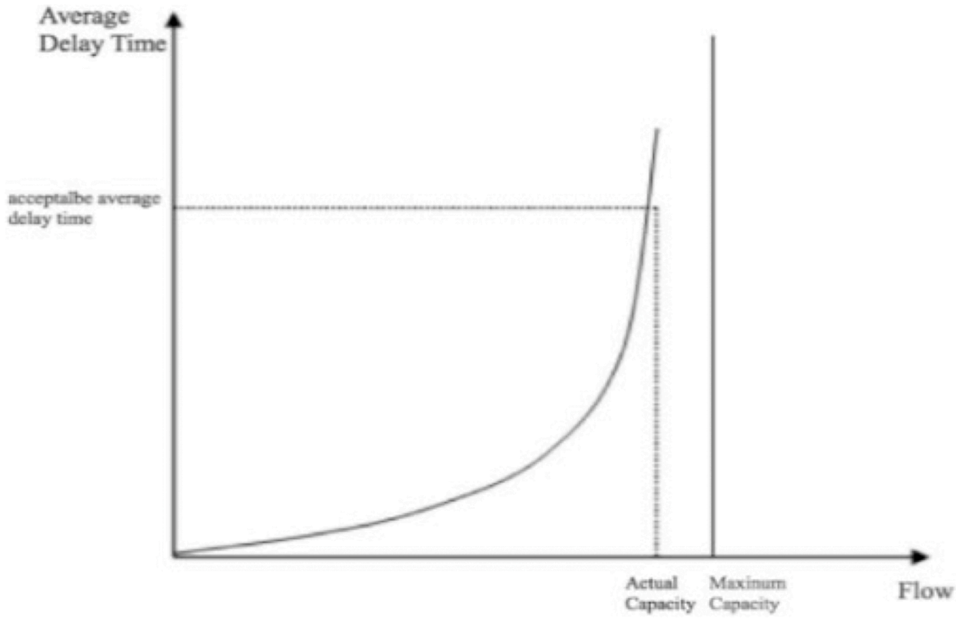


Fig. 11. Relationship between actual capacity and maximum capacity.

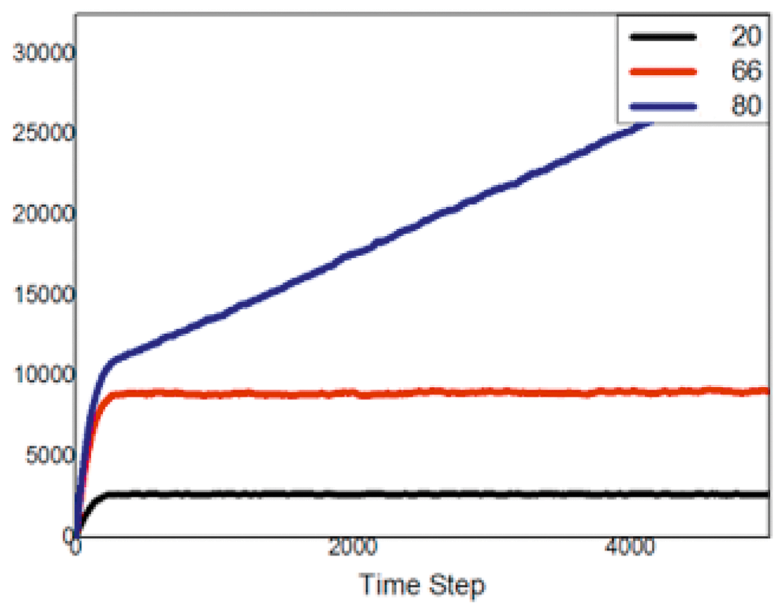


Fig. 12. Number of flights in the network.

point and from Fig. 11, it is the actual capacity of the network.

An order parameter η is presented to observe the phase transition of the network. It is referenced from communication networks and utilized to facilitate computations for ATM networks [16].

$$\eta(p) = \lim_{t\to\infty} \frac{1}{pS} \frac{\langle \Delta N \rangle}{\Delta t} \tag{4.1}$$

N refers to the total number of information packets the unit travels in the communication network that is used in reference), which is flights number in ATM network, and S is the size of the system, which is the sum number of nodes. p is the probability of packet generation per node and time-step, which is the probability of the generation at an airport in one time-step. The power spectrum of the total number of packets is ΔN, and $\Delta N = N(t + \Delta t) - N(t)$. "$< >$" is the average over the time period Δt. Therefore, by observing the parameter, if the generation reaches a limit, the network will have congestion and the parameter will be larger than 0, otherwise, it will be <0, which means the network won't have any congestion. Thus, from Fig. 13, λ_C is the phase transition point and we can find it by formula (4.1).

4.2.2. Theoretical capacity verification

Adapting the order parameter, using ATM network metrics, an order parameter for the ATM network is created:

$$\eta(\lambda) = \lim_{t\to\infty} \frac{C}{\lambda M} \frac{\langle \Delta N_\lambda \rangle}{\Delta t}. \tag{4.2}$$

C is the maximum capacity of a node, which means the maximum number of flights that a node could operate simultaneously. λ is the probability of a node to generate flight, and M is the number of airports in the network. λM the number of flights that are generated per time-

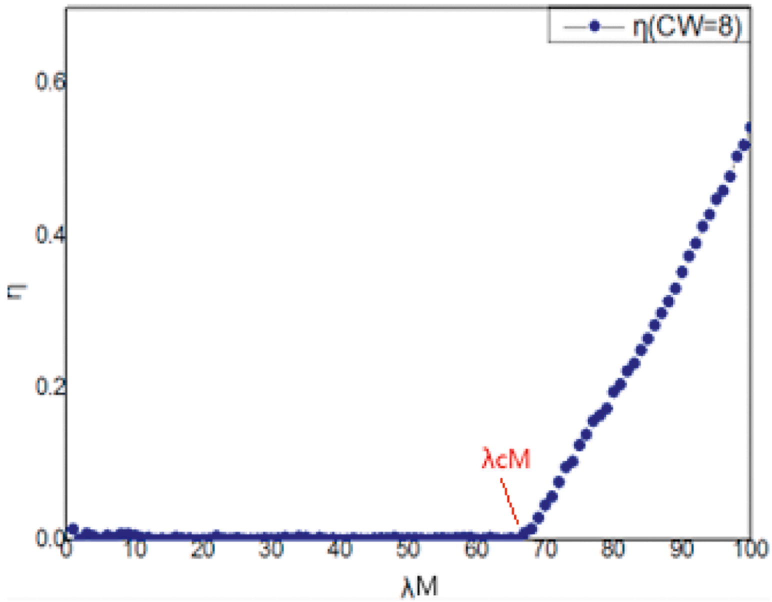


Fig. 13. Phase transition curve.

unit.

When $t \to \infty$, if the network is not congested, i.e. all the flights generated have been operated effectively, the capacity of the network is equal to or larger than λ, therefore $\langle \Delta N_\lambda \rangle = 0$ and $\eta = 0$. Otherwise, i.e. not all the flights generated have been operated effectively, the capacity of the network is smaller than λ, and the network is going to remain congested during Δt. Moreover, the flights would keep accumulating in the network. In this situation, $\langle \Delta N_\lambda \rangle \neq 0$ and $\eta \neq 0$. Then the capacity of the network is

$$\lambda_C M = \max\{\lambda M | \eta(\lambda) \to 0\}. \tag{4.3}$$

Table 4 gives the metrics that are going to be used in the derivation of the reference λ_C [17]. Using the metrics in Table 4, the theoretical capacity can be found. The total betweenness of the network is $\sum_{j=1}^{P} B_j = 2\sum_{j>1} D(i,j)$.

The average shortest path is $D = \frac{2}{M(M-1)} \sum_{j>1} D(i,j)$.

Average flights receiving at node L_{MAX} is $Q_{in} = \lambda_c MDB_{L_{MAX}} / \sum_{i=1}^{P} B_i$, and transferring $Q_{out} = C_{L_{MAX}}$. The condition of congestion occurs is $Q_{in} \geq Q_{out}$. Thus,

$$\lambda_c MDB_{L_{MAX}} \Big/ \sum_{i=1}^{P} B_i = C_{L_{MAX}}. \tag{4.4}$$

From (4) and (5), $\sum_{j=1}^{P} B_j = M(M-1)D$, therefore the theoretical capacity is

$$\lambda_c = C_{L_{MAX}}(M-1)/B_{L_{MAX}}. \tag{4.5}$$

Using the synthetic Chinese network and defining the capacity of every waypoint and that of every airport are the same the phase transition point λ_C is illustrated in Fig. 14, and marked as blue points in Fig. 15, while the red values are theoretical ones from (5). It is obvious that these two values are nearly the same, showing the simulator obeys the basic network theory rules.

Table 4
Metric list.

Metric	Definition
D	Average shortest path of the network (by time-step)
$D(i,j)$	Distance between two nodes (i,j) (by time-step)
B_i	The betweenness at node i(Betweenness is the number of shortest paths that use the node.)
$L_{\max}$	The node has the largest betweenness
Q	Flights' quantity (Q_{in} is for that enter the node and Q_{out} is for that leave the node.)

4.3. Optimization verification

4.3.1. Capacity units' allocation

In Fig. 16, red nodes are the nodes in the network, and the size of each dot indicates its number of connections. The greyscale value indicates the number of flights congested at the node. In Fig. 16**a**, the network is congested at first. In Fig. 16**b**, after shifting some capacity units to the congested node, the greyscale color is lighter, which means the congestion at node is reduced.

5. Typical results

In terms of the resulting performance achieved from the simulation for the network a first achievement is that it indeed works for different input conditions and responds in a calibrated manner. Interestingly, it was also found that the optimal result for a certain set of conditions was not necessarily true for a different set of conditions, in terms of how to manage that, or alternatively, it was found that the management of sector capacity for a small disruption was not equally true for a large disruption. This is perhaps an intuitive result but still interesting and is being investigated in the ongoing use of the network simulation to understand why and also to what degree these factors interact.

5.1. Case study

In a further simplification of the experimental setup for the purpose of this paper, the conditions of the disruption testing were all limited to Sector 20 (a busy sector containing Beijing airport). All disruption lengths were set to three hours and the optimization processes all started from the same capacity allocation, which contained the same total amount of capacity units at 2800, and only the capacity loss differed for each test. Allocations of capacity units were generated according to varying scenarios under investigation, as shown in the rows in Table 5. For example, Row 3 shows that for this situation, a sector is blocked with a capacity loss of 100%. The flights served in the network can be compared to the flights without disruption, where Row 1 is the

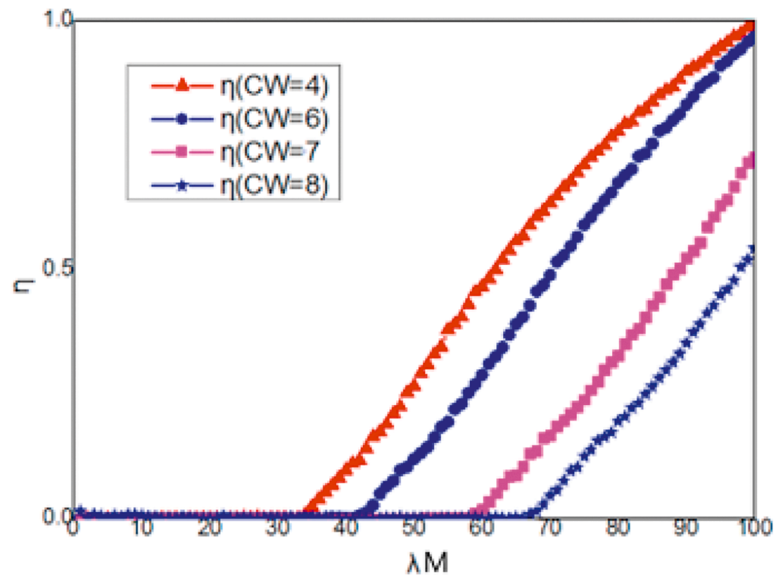


Fig. 14. Phase transition of different Cw.

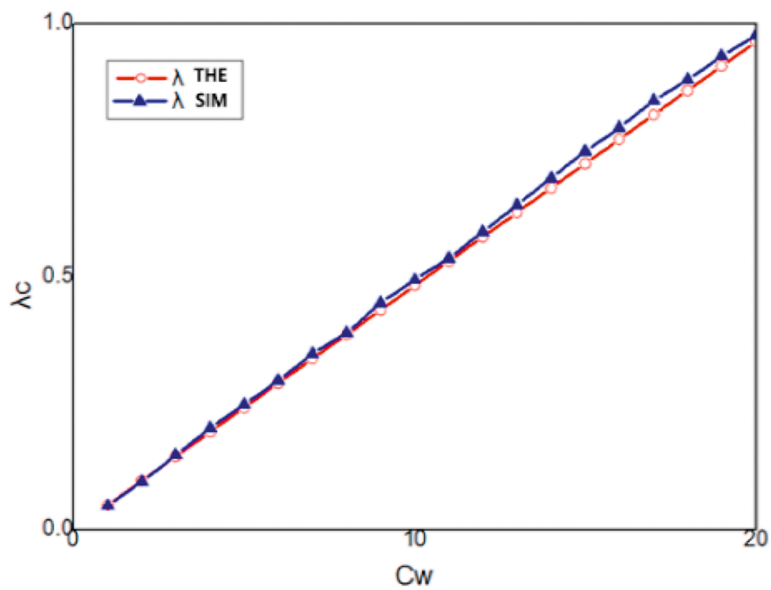


Fig. 15. Theoretical λ_C and simulation λ_C.

reference, and comparing Row 2 and Row 6 for example, shows that the optimization can provide optimal allocation for more flights to be serviced during a disruption. Row 3 and Row 5 show that the optimization process can be controlled and designed in terms of the objective function for different types of disruption.

To understand the impact of the disruption to a single flight, two flights are selected to demonstrate the canceling and changing procedure, shown in Fig. 18 and Fig. 17.

In Fig. 18, the disruption occurred in Sector 2, and it blocked the sector for 180 time units (180 min). The flight was planned to fly from 8 to 0 at the time948. However, destination 0 is in Sector 2 and it was already blocked. The flight would stay at the origin 8, and wait until the area opens again. Since the simulator will serve the flights that were generated earlier, which means those flights that have smaller STDs will have priority in a queue, this one had to wait until at time 1129 to meet the canceling standard CCST (180 min). In this way, the flight was eventually cancelled at the beginning.

In Fig. 17, the disruption occurred in Sector 2, and blocked the sector for 60 time units (60 min). The flight set off before the sector was blocked. When the disruption occurred, the flight was flying. It kept flying to a waypoint and tried to find another airport to wait for another departure. A new destination, airport 1 was found. The flight landed there and waited for the area to open. Then, the flight joined the waiting queue at airport 1, and in the simulator, another flight was generated. Its origin was 1 and destination is 0.

With these two flights, the functions of canceling flights and changing flight worked well. The simulator successfully generated flight information and tracks the flight in the network. In addition, the features of disruptions had different impacts on the network. For these two flights, they have the same (O, D), but one will be cancelled, while the other one can split into two stages to make it to its destination.

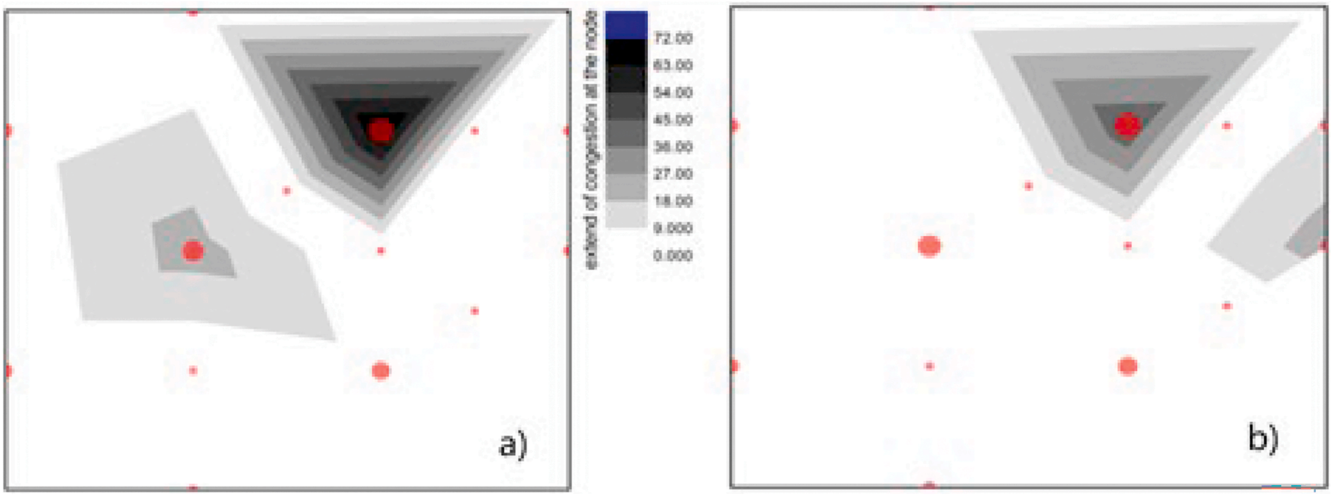


Fig. 16. a) Congestion at node before enhancing capacity b) Congestion at node after enhancing capacity.

Table 5
Network capacity performance impact relative to flight number.

	Generation from Need	Disruption Added	Total Flights Served	Flights Served 100%
1	Origin	No	14,731	100%
2	Capacity loss 100%	Capacity loss 100%	10,384	70%
3	Capacity loss 100%	Capacity loss 50%	11,650	79%
4	Capacity loss 50%	Capacity loss 50%	11,795	80%
5	Capacity loss 50%	Capacity loss 100%	10,027	68%
6	Origin	Capacity loss 100%	9638	65%
7	Origin	Capacity loss 50%	9857	67%

5.2. Influence of different weights

The simulator will produce objectives (see Section 3.2.2) to evaluate the solutions. Fig. 20 are the results of multi-objective evaluation for the network from a number of parallel optimization experiments. It shows the trend of how the objective are getting better and the difference between weights where w stands for w_1, then $w_2=1\text{-}w_1$. As both objectives are normalized, their values only range from 0 to 1 and do not have units. The X-axis is the value of Obj*1,* and the Y-axis is the value of *Obj2.* Different shapes and colors stand for different weights of the objectives. Blue diamond results are those that have $w1=0.7$ and $w2=0.3$. In this case, the simulation prefers solutions prioritizing more flights over lower delay. Red square results are those that have $w1=0.3$ and $w2=0.7$, and solutions tend to have less delay rather than more flights delivered. Green triangle results are those that have $w1=w2=0.5$, which means the simulation will find a balance between delivery and delay. There are three values of w_1 selected. *Obj1* and *Obj2* show a positive correlation. This provides confidence that the simulation provides solutions that have high performance when facing disruptions. But notice in the left corner, there are more red dots. It indicates that, if the user of the simulator wants less delay, then there is a chance of getting a worse result.

Then the simulator can use different combinations of objective functions, and the outcome of the large synthetic network results are plotted according to that shown to the left in Fig. 20 for the range of five alternative scenarios investigated for the network optimization in Table 7, which are Reference Case, (0,1), (0.3, 0.7), (0.5, 0.5), (0.7, 0.3) and (1,0). In the five scenarios (scenarios 2–6), the weight of *Obj1* is gradually increasing, while the weight of *Obj2* is gradually decreasing. There are 50 data points plotted in Fig. 20 and each represents one multi-objective function combination that is generated from one iteration in a 'simulated annealing' optimization implementation for each

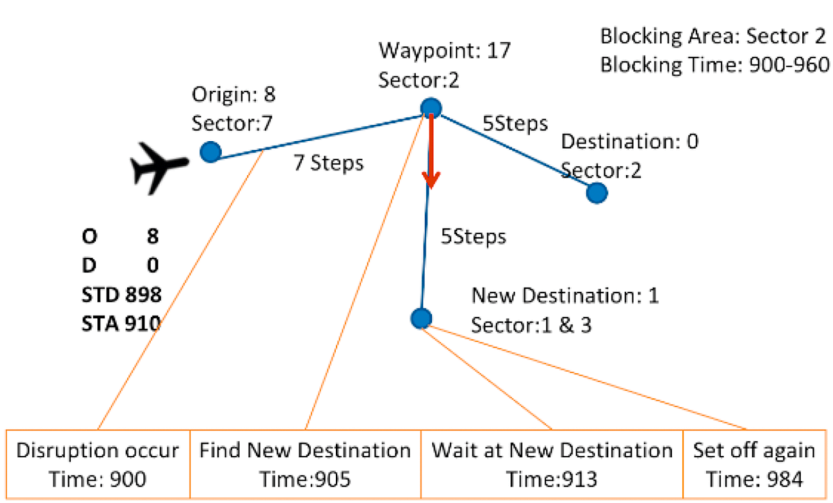


Fig. 17. Time evolution of flight detouring.

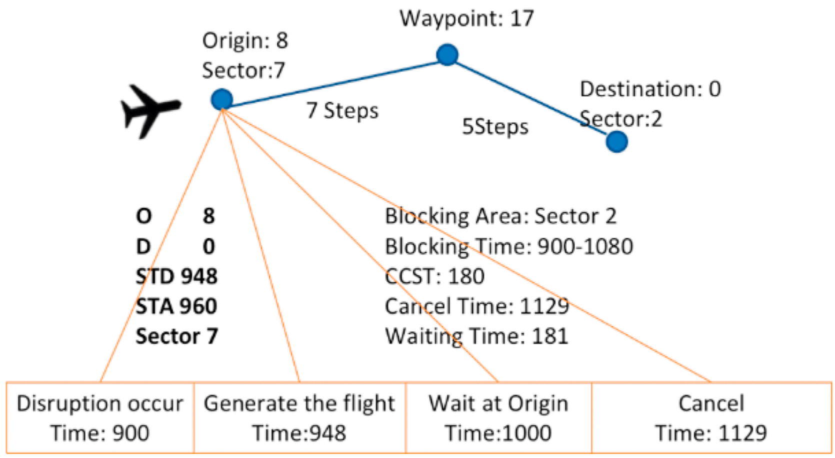


Fig. 18. Time evolution of flight canceling.

combination shown.

As mentioned previously, scenarios 1–5 are the optimal solutions found for the multi-objective function combinations of: (0,1), (0.3, 0.7), (0.5, 0.5), (0.7, 0.3) and (1,0). There is also introduced a solution that allows the network freely to deliver all the flights, but it does not have any optimization process. This solution is noted as the Reference Case (see Table 6). For scenarios 2 and 3, no sector has more capacity units than Reference Case and in 1, 4 and 5, only a few sectors have more capacity units than the Reference Case. Table 6 shows the capacity unit usage for all optimal solutions under different weight combinations and the optimal solutions all have fewer capacity units than the Reference Case, where the total number of capacity units was 3218. It can be seen that the number used in the network is gradually increasing from 2971 to 3048, from the scenarios (0,1) to (1,0). Secondly, there is a evident trend that shows that when Obj1 has a higher weighting, i.e. larger than the Reference Case w1, it is likely to have more capacity units allocated in the network (although not exactly following this rule). Finally, the average reduction is 7% for the sum capacity units used in origin capacity allocation.

Table 7 lists the data of all the sectors in the Synthetic Chinese Network. In this table, the Average column presents each sector's overall capacity relative to the Reference Case across the five optimal solutions corresponding to different (w_1, w_2) combinations. The column "Number of Scenarios ≥95%" means that the sector has >95% capacity units of Reference Case in different (w_1, w_2) scenarios. As there are five combinations of (w_1, w_2), which are listed in Table 6, apparently, this value cannot be more than five. Using 95% here is because those sectors with values over 100% (Sector 14, 25 and 28) do not show very clear conclusions, and more sectors can help to demonstrate the rules in the simulation. Column 'airports' indicates the number of airports in this sector. Column 'connections' is the number of connections that the sector has. 'Traffic' is the number of flights crossing, generated and landing in the sector. Traffic per unit is traffic divided by the Reference Case capacity of the sector, which can be taken as the traffic load in the sector. For example, the average capacity in the five scenarios (1–5 in Table 6) of Sector 1 is 44% of the Reference Case, and none of the capacity is equal or higher than 95% of the Reference Case. For example, for Sector 6, the average capacity of Scenarios 1–5 in Table 6 is 96% of Reference Case and four scenarios are using equal or higher than 95% capacity units of the Reference Case.

Sectors 6, 8, 13, 14, 15, 23 and 26 have average capacity greater than 95%. Note that Sector 25 and 28 are not included, but Sector 26 is a

Table 7
Sector performance in disruption.

Sector	Average	No. of Scenarios ≥95%	Airports	Connections	Traffic
1	44%	0	2	36	10
2	83%	0	5	89	83
3	87%	0	8	139	225
4	76%	0	3	46	86
5	84%	0	3	71	401
6	96%	4	15	416	5402
7	93%	2	6	89	468
8	96%	4	8	275	3577
9	91%	0	2	34	239
10	94%	3	2	44	565
11	92%	1	2	61	559
12	79%	0	2	63	652
13	96%	3	6	124	1369
14	96%	4	6	110	286
15	97%	5	5	128	1270
16	93%	1	4	73	632
17	94%	2	5	87	581
18	92%	1	4	82	421
19	81%	0	4	42	157
20	92%	1	5	227	871
21	92%	1	3	62	248
22	91%	0	6	120	557
23	95%	3	11	224	1479
24	94%	2	13	164	773
25	94%	3	2	36	75
26	96%	4	7	213	351
27	94%	2	6	160	732
28	92%	2	5	52	59

Table 6
The impact of different weights on objectives.

Scenario	w1	w2	Capacity Sum	Capacity Difference	Reduced Units	Iterations of SA process	Iteration to Optimal	Obj1	Obj2	Obj	Objective Enhancement		
Reference			3218	0	0	0	0	0.91577	0.77957		Obj1	Obj2	Obj
1	0	1	2971	−247	8%	23.3	16.7	0.95670	0.79984	0.79984	4.5%	2.6%	2.6%
2	0.3	0.7	2962.25	−255.75	8%	22.0	11.7	0.95657	0.79934	0.84651	4.5%	2.5%	3.2%
3	0.5	0.5	2971.5	−246.5	8%	23.3	11.3	0.95574	0.79924	0.87749	4.4%	2.5%	3.5%
4	0.7	0.3	2993.75	−224.25	7%	22.0	12.7	0.95761	0.79953	0.91018	4.6%	2.6%	4.0%
5	1	0	3048.25	−169.75	5%	18.7	10.7	0.95760	0.79902	0.95760	4.6%	2.5%	4.6%

sector that located at the edge of the network. This suggests that when designing a better network structure, we should pay attention to the sectors at the edge of the map but only those are not enough. In more than three combinations of (w_1, w_2), they have >95% capacity of the Reference Case. Most of them have a larger number of airports. In Sector 6, 8 and 23, they have airports of CATE1 (top 10 busiest airports in China). It can also be seen that these three sectors have the most traffic among all sectors in the network. In addition, they tend to have more connections. Sector 13, 14 and 15 are next to each other (see Fig. 19). Taking them together as one area, it is surrounded by Sector 6, 8, and 23. Sector 14 is in the center of Sector 6, 8, 13 and 15. Therefore, Sector 14, which should have more capacity, is the one linking these sectors together and should gain more attention.

From the traffic data in the sectors, Sector 6 (three top 10 busies airports) and 8 (two top 10 busiest airports) are much higher than others. Sector 23 (two top 10 busiest airports) are also operating a relatively large amount of traffic. These three sectors have seven out of ten busiest airports in China. They together form an area (together with Sectors 13, 14 and 15) that requires high capability to operate traffic.

For the design of an optimal network structure, regarding capacity allocation, the sectors that have high traffic demand should be taken into consideration. Meanwhile, the neighboring sectors with busy airports should also be focused on as those sectors' capacity units are the main constraint to enhance the network performance. In addition, it also needs to be made aware that some of the sectors on the edge of the network can be increased to get better performance. With the help of the simulation tool, we can observe the traffic and the relationship between traffic and the capacity of the sectors. Thus, the distribution of capacity, which is the input resource for each sector, can be obtained as expected by using the weighted objective method.

6. Transdisciplinarity of ATM networks

The main aim of this paper was to present the ATM Network model/simulation to illustrate dimensions, criteria related to

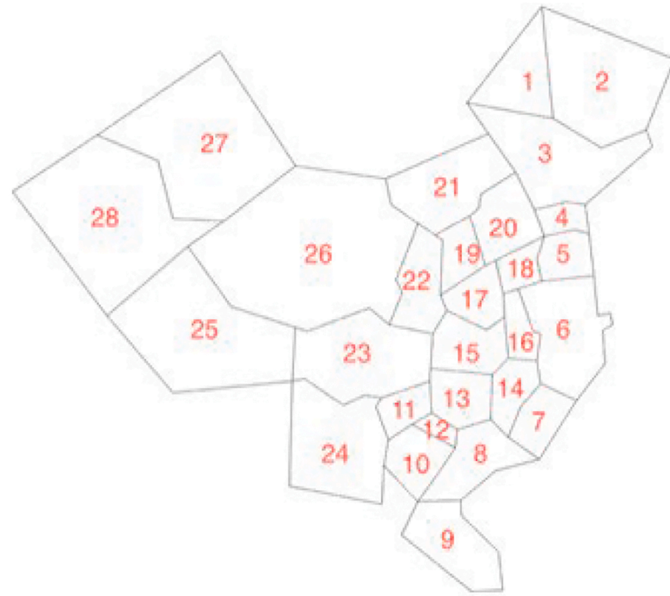


Fig. 20. Sector map.

Transdisciplinarity through the simulated metrics relating to Robustness and Resilience [18–21] as encapsulated by the framework presented in Fig. 21 [22].

In Table 8**,** the transdisciplinary process of the simulation tool that is presented in this paper is clearly explained.

The network simulation tool can be used in the ATM network context to verify the traffic flow performance and robustness and resilience relative to the network behavior and analysis understanding. Fig. 22 presents the understanding of the generic behavior of a system relative to robustness and resilience. The network will have a decrease of

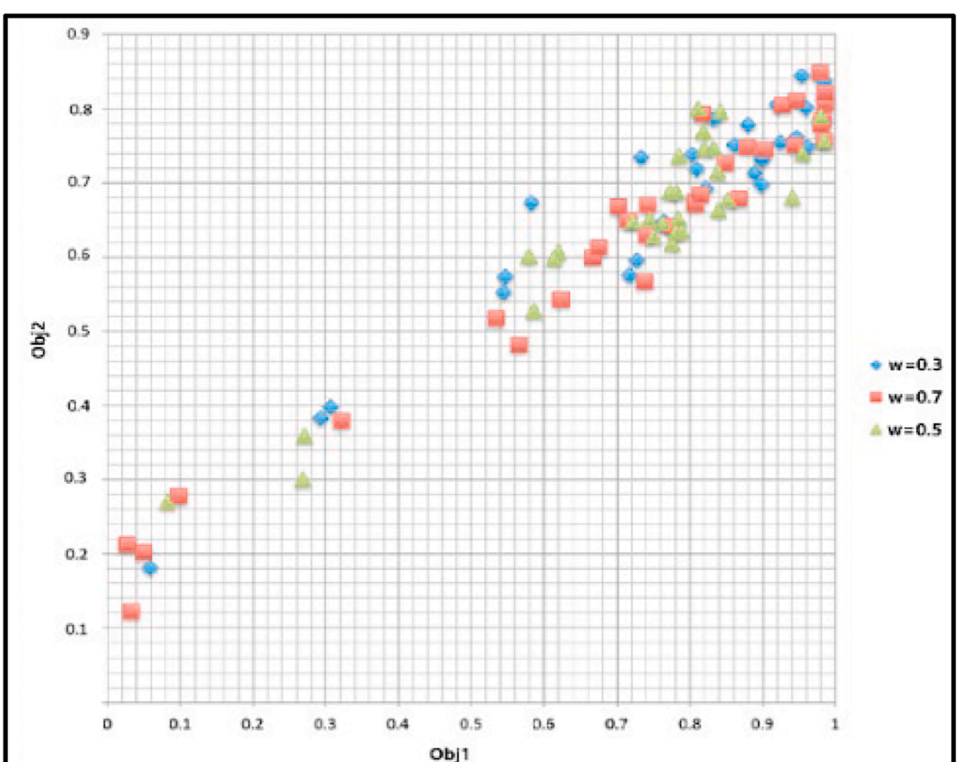
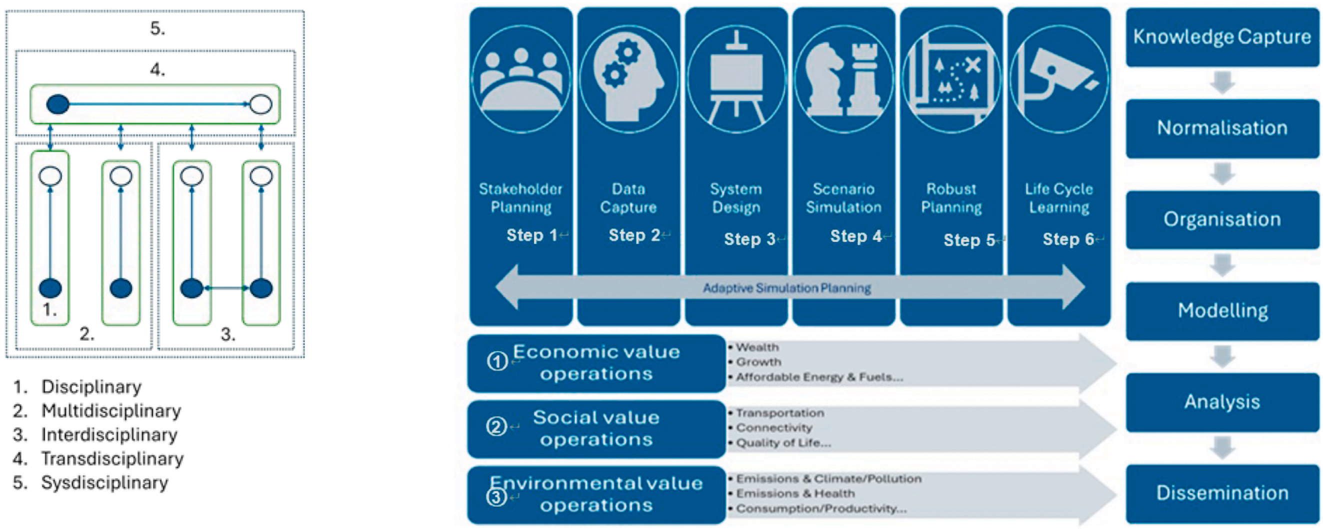


Fig. 19. Testing multi-objective results.



a) b)

Fig. 21. a) Principles of transdisciplinarity and b) Transdisciplinary process integration (Curran, 2024).

Table 8
Implementation of the transdisciplinary process for ATM simulation (with reference to Fig. 21b).

	Transdisciplinary Process	Air Traffic Network Simulation Tool Features
Step 1	Stakeholder Planning	Airline; Airports; Passengers; Regional/National Goal
Step 2	Data Capture	Real/Synthetic Network Data
Step 3	System Design	Network Modelling and Simulation Tool Setup
Step 4	Scenario Simulation	Simulation of fight operations, flow analysis and impact reaction
Step 5	Robust Planning	Robustness and Resilience of the Network
Step 6	Life Cycle Learning	Projection and Implication

performance when facing an impact at t_0 and theoretically fully recover at t_1. The ATM network simulator can record all the changes and compare with the ultimate performance of the system relative to the drop in performance associated with the key performance indicators selected through the process presented in Fig. 21b. Thus, the objective function in Section 3.2.2 can be measured with a normalized metric that is associated with the three interconnected sustainability criteria for further analysis and transdisciplinary system understanding. Therefore, in terms of future work on this model, robustness and resilience will be used as the transdisciplinary system performance criteria of such an ATM network. The two proposed transdisciplinary criteria, robustness and resilience, represent the decline and restoration of the system's performance as analytically quantified using the simulation model to provide system design metrics. The model is capable of tracing the impact from disruption to a network and therefore, these features and characteristic can be captured for further analysis, understanding and design purposes.

With reference to Fig. 21, the simulation maps the simulated outputs and transdisciplinarity as measurable analytical characteristics in Fig. 22. In Fig. 22, the simulation has 1440 time-steps, which indicate 24 h for the simulated network when Sector 20 (see Fig. 19) is blocked. It can be seen there is a 15% decrease in performance which is in respect to delay and that the recovery time is relatively linear in returning back to the original level. The performance is the normalized indicator, and it ranges from 0 to 1. Sector 20 is blocked for 3 h in the simulation process. The figure shows how the performance drops and recovers quickly at first, and then linearly and the recovery time is approximately 3.5 h. The shaded triangle represents the loss of performance, which helps the analyst to understand the network behavior. In terms of performance, this represents the three transdisciplinary dimensions in Fig. 21b The environmental loss is being implied through the need for passengers

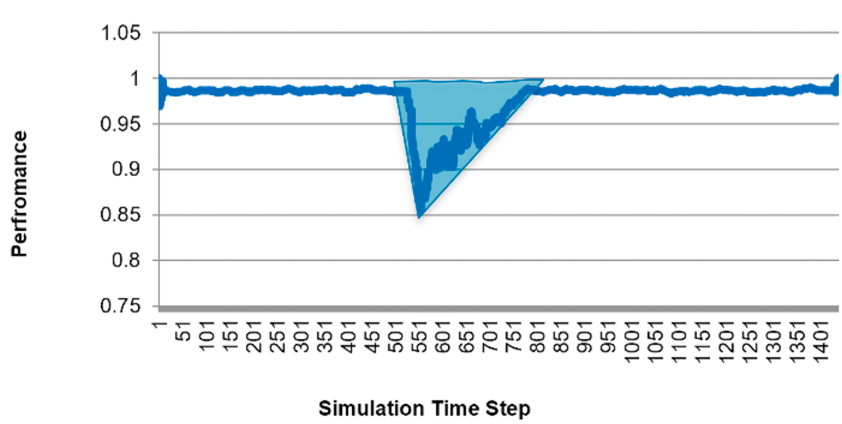


Fig. 22. Simulation result of performance.

who find a new solution to their travel problem and the associated inefficiency and waste arising from the sector blockage. The transdisciplinarity criteria of robustness *Rbst* and resilience *Rsil* can be analytically defined by the following metrics:

$$Rbst = \frac{P_1 - P_0}{P_0} \tag{6.1}$$

$$Rsil = \frac{P_2 - P_1}{P_1} \bigg/ \frac{T_2 - T_0}{T_0} \tag{6.2}$$

Where T0 is the time at which the disruption occurs, T1 is the time at lowest performance and T2 is the time reach recovery or stability, while P0, P1 and P2 are the associated levels of performance.

In Table 9 C1 refers to the case displayed in Fig. 23 while C2 and C3 highlight the impact of a shorter or longer time step for recovery and therefore increasing or decreasing resilience respectively. Cases C4 and C5 present the change in robustness if performance degradation is less of more respectively, leading to an increase and decrease in robustness respectively. In conclusion, these transdisciplinary metrics can be used in the analytical performance and characteristic of system performance, such as that for the ATM network application addressed in this paper.

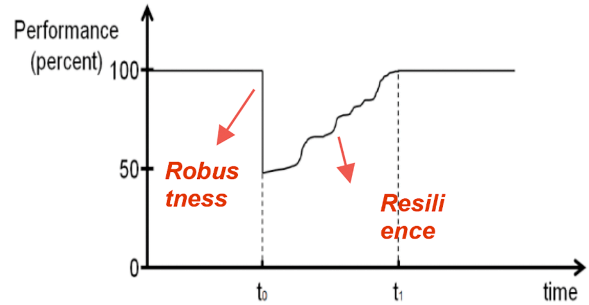


Fig. 23. Robustness and resilience of a system.

7. Conclusion

7.1. Conclusion

Notably, this simulation is empowered by **Industrial Information Integration (III)**'s heterogeneous industrial resource integration capability, which unifies discrete design parameters (aircraft, airports, ATM routes) into a digitalized transdisciplinary framework, aligning with the fundamental tenements of **Transdisciplinary Process Integration (TPI)**—this not only resolves the core pain point of fragmented data and incompatible domains in traditional ATM simulation but also verifies TPI's practical applicability in complex industrial systems, forming a closed loop of "technology empowerment-theory verification-industrial application". Enabled by III's data standardization and cross-domain information synergy, the tool effectively bridges the gap between domain-specific requirements (e.g., airline efficiency, airport capacity, air traffic safety) and system-level performance, which is a key added value that traditional simulators lack.

In terms of the realistic systems design of the Network and associated model: (1) Results from the optimization proved that the optimization works as expected, which means, the network structure from the optimal results will provide optimal performance in terms of realizing the objectives. (2) The verification allows the simulator to produce stable and reliable results and also, provides support to find network structure that meets transdisciplinary user demands. In terms of the effectiveness of the simulation to capture the behavior of the network: (3) The simulator will provide solutions that meet the needs. i.e., let the objective of larger weight has better performance. (4) Sectors that have large traffic demand, sectors that adjacent to sectors with busy airports and sectors on the edge of the network may require more capacity units to have better performance.

In terms of verification, a three-tiered verification is presented in order to help confirm the simulator's functionality and reliability, via transdisciplinary integration of aviation engineering, computer simulation, and optimization theory. (5) Programming Verification: The random number seed independence and consistent scenario results confirm the cross-disciplinarily integrated code's reliability. (6) Network Verification: Integrating communication network traffic modeling and network dynamic analysis, phase transition behavior and single/multi-disruption tests validated traffic performance alignment with real-world rules. (7) Optimization Verification: Capacity adjustments meet the expected performance/traffic changes, and scenario-specific disruption solutions verify tailored optimal strategy generation.

In terms of results and the ultimate performance of the model: (8) It can be found that schedules of the real networks meet the need in real life and has the potential to allow users of the simulator change their demand when meeting different needs or crisis. This flexibility is supported by III's dynamic information integration, which adapts to transdisciplinary changes and validates the network's transdisciplinary adaptability. (9) Each iteration takes similar time, which means the process is independent, i.e. the solution from the output suits all disruptions that set in the simulator. This allows users to find a network structure that can handle the crisis or meet particular need. (10) For the distribution of capacity units, the total capacity units do not need to be the largest to obtain the optimal results, instead, it depends on III-driven transdisciplinary capacity allocation—balancing efficiency and resilience. This paper also culminated in an analysis of the transdisciplinarity of the 'typical' form of the ATM network analysis research presented. This was evident from the disciplinarity reflections, and established the fundamental relevance and alignment with the fundamental tenements of Transdisciplinary Process Integration (TPI). It was highlighted that an aircraft's daily utilization would be of the order of 16 h and, therefore, the projection of the network resilience will impact on 25% of the airlines' and airports daily utilization.

In conclusion, it was shown that the ATM network example shown is highly transdisciplinary in nature and consequently provides a useful example from the field of Transdisciplinary Engineering and more importantly helps verify some of the fundamentals, principles and concepts being developed to help define this developing field by leveraging industrial information integration capabilities, thus expanding the application boundaries of III to complex service-oriented industrial systems.

7.2. Limitation

In terms of the realistic systems design of the Network and associated model: (1) Certain network features (see Table 2) are required for input and all the inputs of networks need adaptation beforehand. (2) Due to the limited data resources, the verification has only been conducted in several networks.

In terms of the effectiveness of the simulation to capture the behavior of the network: (3) The traffic for simulating is limited in one day due to the computing time constraints of hardware. There is a possibility that long-term traffic input will provide more notable results for discussion. (4) Capacity relocating methods are relatively simple and completely depend on the workload of the sector. The influences of some geographic

Table 9
Metrics for robustness *Rbst* and resilience *Rsil*.

CASE	T0	T1	T2	P0	P1	P2	Rbst	Rsil
C1	500	553	770	1	0.85	1	−0.15	0.33
C2	500	553	661.5	1	0.85	1	−0.15	0.55
C3	500	553	987	1	0.85	1	−0.15	0.18
C4	500	540	987	1	0.9	1	−0.1	0.11
C5	500	600	987	1	0.65	1	−0.35	0.55

information are ignored to reduce the complexity of modelling.

In terms of results and the ultimate performance of the model: (5) The simulation can not only output the objectives but also record all traffic information throughout the entire process. Therefore, the selection and analyzation process has to be transfered into other platforms. (6) The solution evolving and converging process are controlled by end criteria. There is a possibility that the simulation will discover one or more better solutions.

In this paper, most of the limitations of the simulation tool stem from simplifying the code to control computing costs and coding hardware constraints. However, this simplification also enables the tool to improve problem-solving efficiency and allows it to adapt to multiple network types.

7.3. Future work

The future work will still focus on exploring the application possibilities of this simulation tool, with a focus on deepening the integration of Industrial Information Integration and transdisciplinarity. Specifically, it will analyze the robustness and resilience of the network, as mentioned in Fig. 23, and the relationship between them and the network when facing disruptions, together with the network characteristics and network performance by integrating transdisciplinary disruption factors through III's enhanced cross-domain information synergy The simulator will provide figures like Fig. 23 to visualize the drop in of performance and the recovery of the network for further study based on high-precision data integration, which realizes micro-level transdisciplinary interaction analysis.

Moreover, output results of the simulation can also be refined to individual sectors and even flights to fully leverage the simulation tool's advantage in capturing the detailed information and movement of the network traffic flow. This will provide a better understanding of the traffic flow and the impact on a small unit of the network, as shown in Fig. 18 and Fig. 17.

Additionally, other networks different from air traffic networks will possibly be used for analysis to verify the tool's adaptability to other network types and help to conduct analytical verification from the perspective of theoretical models.

CRediT authorship contribution statement

Richard Curran: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Formal analysis, Conceptualization. **Yalin Li:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Xiaojia Zhao:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Supplementary descriptions of transdisciplinary engineering theory

With reference to the Principles of Transdisciplinarity, the ATM Network modelling and simulation that was presented as representative withing the technical system design [20–23], analysis and control fields does follow all of the principles outlined in Fig. 21a [22]. The characteristics of multidisciplinarity (2) are evident through the performance of an aircraft in terms of Aircraft Velocity is used as well as the spatial Distance Between Airports in the Network for example; where one model (1) does not necessarily influence the performance of the other (1) but both (2) are used in calculating a common performance criteria such as Infrastructure Cost; being a simple amalgamation of either models value in the respect. However, these two models are also used in an Interdisciplinary (3) manner where the velocity of the aircraft is now used by the simulation of the Network in the simulation in order to calculate the Route Times Between Airports, the Network Capacity that can be achieved in a certain timeframe for that ATM network, and the Delay Time resulting from a given network disruption. Furthermore, the overarching model of the ATM model and associated simulation, which was used to run the real scenarios, forms the Transdisciplinary (4) layer [22,24] that integrates all of the other formulations and combines these into indeed a common Transdisciplinary Goal that is elevated above all other subservient lower-level system goals; the later for clarity being for example the Aircraft System (model), or Airport, or Air Traffic Network, etc.

One can also use the Transdisciplinary Process Integration (TPI) framework presented in Fig. 21b by Curran [22] in order to assess the ATM modelling and simulation process presented here-in terms of the Transdisciplinary Engineering metrics associated with the proposed Robustness and Resilience criterias. This is a complex integrated framework of Transdisciplinarity that has been proposed and is more fully presented in Curran [22] but essentially it combines the processes of Adaptive Simulation Planning [25–30], Multi-attribute Value Analysis [27,28], and Knowledge Management [31]; as shown by the top-left, bottom-left, and right-hand sections of Fig. 21. The ATM Network case study presented herein is easily associated with the *System Design* and *Scenario Simulation* steps shown in Fig. 21 as part of the *Adaptive Simulation Planning*, as part of the *Transdisciplinary Engineering Integration (TDI)* process shown. However, although the Stakeholder Planning and Data Capture phases were not highlighted in this paper, those were followed, as would be typical, in an informal way to scope out the 'project brief' and determine the goals and ultimate research output and application impact, the latter being associated with the beginning of the Value Analysis process – as a fundamental part of the multi-objective analysis approach [32–37]. Implementation will include the *Robust Planning* for the actual application in some sort of design effort, intervention or control. The latter is very directly associated with the monitoring and *Life Cycle Learning* phase [38–40]. All processes mentioned, both those that are presented horizontally and vertically in Fig. 21b, are supported by the Knowledge Management process highlighted on the righthand side in the Figure. For clarity, *Normalisation* refers to the calibration and processing of core data bases, and *Organisation* refers to the structuring of these resulting data and knowledge bases through ontological and highly defined standardized 'knowledge forms'. Finally, following the better recognized phases within the KNOMAD methodological process that are *Modelling* and *Analysis* (closely aligned and forming an 'axis' with the *System Design* and *Scenario Simulation* of the ASP), there is the *Dissemination* phase and effort which also includes tool development, process formulation, methods, etc. for the dissemination through the business process where relevant.

The simulation tool aims to explain network behavior and provide a reasonable solution for network stakeholders (Step 1) with differing goals, as referenced to the three value criteria in Fig. 21b that are the pillars of sustainability. The main stakeholders, airlines, airports, passengers and regional or national associations, do have different goals, and the virous data need to collected to build the models associated with the system (Step 2). In Fig. 21b, the righthand side represents the innovative Knowledge Based Engineering (KBE), also formulated as the KNOMAD process [39]. The KNOMAD process recommends the associated steps with gathering relevant information, collaborating and cleaning the data, structuring and building models that can be disseminated for system scenario generation (Step 3 & Step 4). Basically, the three main pillars of sustainability are economic, social and environmental values, as highlighted in Fig. 21b. This also refers to the transdisciplinary highlighted in Fig. 21a where the values are inherently cross-disciplinary. Fig. 21a highlights that system-of-systems performance requires transdisciplinary integration. Fundamentally, this network model shows how the various disciplines have to be considered in the complex example of an air transport network. failure in a traffic network will result in a loss of these three shared sustainability/-transdisciplinary dimensions. For instance, a blocking airport that closed suddenly will lead to several consequences, like profit loss for airlines and the airport, while, for passengers, extra time cost may cause social problem and emissions from the alternative traffic methods required. Relative to Fig. 21b, Step 5 is the application of the results from the network simulation tool to better ensure the robust performance of the network. In this respect, Step 5 refers to both the robustness, ability to maintain performance, and resilience, ability to recover from loss of performance. Based on the real network traffic data, the synthetic network is generated to help establish the simulation's reliability and verification. Consequently, the network modelling is relatively simple but encompasses the function of illustrating network behavior and the associated flight operations. This ensures the time-saving requirement of the simulation tool for the network analyst. Also, the weighted objective function allows the analyst to give priority to the performance factor that they want to prioritize. In terms of the scenario simulation (Step 3), the disruptions are from the real impact of the ATM network. The simulator will provide a record of the flights and generate results to help the analyst to understand the performance of the network and obtain balanced solutions. With the help of the tool, the projection of the network design and performance implication (Step 6) from the network behavior will help the network analyst to embrace life cycle learning.

Data availability

Data will be made available on request.

References

[1] Y. Li, B.F. Santos, R. Curran, ATM network performance evaluation and optimization using complex network theory, in: *Conference Proceedings: Air Transport and Operations Symposium 201*5, Delft, The Netherlands, 2015, https://doi.org/10.13140/RG.2.1.1043.6968.

[2] C. Huang, S. Fang, H. Wu, Y. Wang, Y. Yang, Low-altitude intelligent transportation: system architecture, infrastructure, and key technologies, J. Ind. Inf. Integr. 42 (2024) 100694, https://doi.org/10.1016/j.jii.2024.100694. ISSN 2452-414X.

[3] S. Yin, N. Zhang, H. Dong, Preventing COVID-19 from the perspective of industrial information integration: evaluation and continuous improvement of information networks for sustainable epidemic prevention, J. Ind. Inf. Integr. 19 (2020) 100157, https://doi.org/10.1016/j.jii.2020.100157. ISSN 2452-414X.

[4] B.F. Santos, M.M. Wormer, T.A. Achola, R. Curran, Airline delay management problem with airport capacity constraints and priority decisions, J. Air Transp. Manag. 63 (2017) 34–44.

[5] R. S. Bouarfa, H.A. Blom, R. Curran, M.H. Everdij, Agent-based modeling and simulation of emergent behavior in air transportation Complex Adapt. Syst. Model. (1) (2013) 1–26.

[6] V. Ho-Huu, S. Hartjes, H.G. Visser, R. Curran, An optimization framework for route design and allocation of aircraft to multiple departure routes, Transp. Res. D: Transp. Environ. 76 (2019) 273–288.

[7] S. Janssen, A. Sharpanskykh, R. Curran, AbSRiM: an agent-based security risk management approach for airport operations, Risk Anal. 39 (7) (2019) 1582–1596.

[8] F. Herrema, R. Curran, H.G. Visser, D. Huet, R. Lacote, Taxi-out time prediction model at Charles de Gaulle airport, J. Aerosp. Inf. Syst. 15 (3) (2018) 120–130.

[9] X. Jiang, X. Wen, M. Wu, M. Song, C. Tu, A complex network analysis approach for identifying air traffic congestion based on independent component analysis, Phys. A: Stat. Mech. Appl. 523 (2019) 364–381, https://doi.org/10.1016/j.physa.2019.01.129.

[10] A. Arenas, Iacute, A. Az-Guilera, et al., Communication in networks with hierarchical branching, Phys. Rev. Lett. 86 (14) (2001) 3196.

[11] K.-Q. Cai, J. Zhang, W.-B. Du, X.-B. Cao, Analysis of the Chinese air route network as a complex network 2012, Chin. Phys. B 21 (2012) 028903, https://doi.org/10.1088/1674-1056/21/2/028903.

[12] Civil Aviation Administration of China (CAAC), Flights waiting in the air, from, http://www.caac.gov.cn/GYMH/MHBK/KZJT/201509/t20150923_1899.html, 2015. Accessed 18 April 2026.

[13] N. Wognum, Transdisciplinary engineering systems, in: R. Kenett (Ed.), Systems Engineering in the Fourth Industrial Revolution: Big Data, Novel Technologies, and Modern Systems Engineering, 2020, pp. 483–510.

[14] S. Kirkpatrick, C.D. Gelatt, M.P. Vecchi, Optimization by simulated annealing, Science 220 (4598) (1983) 671–680.

[15] J. Zhang, Morden Air Traffic Management, 9, Beihang University Press, Beijing, 2005, p. 279.

[16] A. Arenas, Iacute, A. Az-Guilera, et al., Communication in networks with hierarchical branching, Phys. Rev. Lett. 86 (14) (2001) 3196.

[17] W.-X. Wang, B.-H. Wang, C.-Y. Yin, Y.-B. Xie, T. Zhou, Traffic dynamics based on local routing protocol on a scale-free network, Phys. Rev. E 73 (2006) 026111.

[18] A. Majumdar, J. Polak, Estimating capacity of Europe's airspace using a simulation model of air traffic controller workload, Transp. Res. Rec. 1744 (1) (2001) 30–43.

[19] A. Majumdar, J. Bentham, M. Richards, En-route sector capacity estimation methodologies: an international survey, J. Air Transp. Manag. 11 (6) (2005) 375–387.

[20] M. Vert, A. Sharpanskykh, R. Curran, Adaptive resilience of complex safety-critical sociotechnical systems: toward a unified conceptual framework and its formalization, Sustainability 13 (24) (2021) 13915.

[21] D.J. Lang, A. Wiek, M. Bergmann, M. Stauffacher, P. Martens, P. Moll, C.J. Thomas, Transdisciplinary research in sustainability science: practice, principles, and challenges, Sustain. Sci. 7 (2012) 25–43.

[22] R. Curran, Foundations of transdisciplinary engineering theory: sustainable airport application. Advances in Transdisciplinary Engineering, UCL East, London, 2024, pp. 694–707, https://doi.org/10.3233/ATDE240920.

[23] M.H. Guimarães, C. Pohl, O. Bina, et al., Who is doing inter- and transdisciplinary research, and why? An empirical study of motivations, attitudes, skills, and behaviours, Futures 112 (2019) 102441.

[24] Hsu, R. Curran, *Advances in Systems Engineering* (Vol. 252), American Institute of Aeronautics and Astronautics Inc. (AIAA), 2016, https://doi.org/10.2514/4.104091. Print ISBN: 978-1-62410-408-4; Electronic ISBN: 978-1-62410-409-1.

[25] J. Stjepandić, N. Wognum, W.J.C. Verhagen, Systems Engineering in Research and Industrial Practice: Foundations, Developments and Challenges, Springer International, Cham, 2020.

[26] M.A. Max-Neef, Foundations of transdisciplinarity, Ecol. Econ. 53 (1) (2005) 5–16.

[27] W.J.C. Verhagen, B. De Vrught, J. Schut, R. Curran, A method for identification of automation potential through modelling of engineering processes and quantification of information waste, Adv. Eng. Inform. 29 (3) (2015) 589.

[28] M.G. Lawrence, S. Williams, P. Nanz, O. Renn, Characteristics, potentials, and challenges of transdisciplinary research, One Earth 5 (1) (2021) 2022.

[29] J.W. Hall, R.J. Lempert, A. Keller, A. Hackbarth, et al., Robust climate policies under uncertainty: a comparison of robust decision making and info-gap methods, Risk Anal. 32 (2012) 16527–16672.

[30] W.E. Walker, M. Haasnoot, J.H. Kwakkel, Adapt or perish: a review of planning approaches for adaptation under deep uncertainty, Sustainability 5 (2013) 955–979.

[31] R. Curran, S. Castagne, J. Early, M. Price, S. Raghunathan, J. Butterfield, A. Gibson, Aircraft cost modelling using the genetic causal technique within a systems engineering approach, Aeronaut. J. 111 (1121) (2007) 409–420.

[32] R. Curran, S. Raghunathan, M. Price, Review of aerospace engineering cost modelling: the genetic causal approach, Prog. Aerosp. Sci. 40 (8) (2004) 487–534.

[33] R. Curran, W. Beelearts, T. Abu-Kias, M.J.F. Repco, Y.L.J. Sprengers, P.N.C.S. van der Zwet, Value operations methodology (VOM) applied to medium-range passenger airliner design, J. Aerosp. Oper. 1 (1–2) (2011) 3–27.

[34] R. Curran, W.J.C. Verhagen, M.J.L. Van Tooren, T.H. Van Der Laan, A multidisciplinary implementation methodology for knowledge-based engineering: KNOMAD, Expert Syst. Appl. 37 (11) (2010) 7336–7350.

[35] R. Curran, J.K. Knoester, E. Bavelaar, A value operations methodology framework to strategically rank sustainable airport innovations, in: 17th AIAA Aviation Technology, Integration, and Operations Conference, 5-9 June 2017, Denver, Colorado, AIAA AVIATION Forum, 2017.

[36] V. Belton, A comparison of the analytic hierarchy process and a simple multi-attribute value function, Eur. J. Oper. Res. 26 (1) (1986) 7–21.

[37] T.J. Stewart, A critical survey on the status of multiple criteria decision making theory and practice, Omega 20 (5–6) (1992) 569–586. Issues.

[38] R. Curran, Value operations methodology (VOM) applied to medium-range passenger airliner design, J. Aerosp. Oper. 1 (2012) 3–27.

[39] F.H. Barron, Selecting a best multiattribute alternative with partial information about attribute weights, Acta Psychol. 80 (1–3) (1992) 91–103. Issues.

[40] F.H. Barron, B.E. Barrett, Decision quality using ranked attribute weights, Manag. Sci. 42 (11) (1996) 1515–1523.