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Review on Meta-heuristics Approaches for Airside Operations Research

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Abstract

The number of publications related to airside operations research is increasing and gaining in popularity. This paper aims to provide researchers with a comprehensive and extensive overview of meta-heuristics application for aviation research, with a particular focus on the airside operations. The scope of airside operations research covers airspace and air traffic flow management, aircraft operation in the terminal manoeuvring area and surface traffic operation. Based on the recent publications related to airside operations, the meta-heuristics approach is a promising approach to enhance the computational efficiency and achieve higher applicable in various decisions in airside operations. However, the literature on airside operations research is quite disjointed and disparate. Therefore, a general taxonomy framework for the airside information system is proposed in order to classify the research systematically and expedites related research and development of engineering applications in the aviation industry. To the best of our knowledge, this is the first review of the field using the meta-heuristics approach. The prominent findings of recent publication and the directions of future research are addressed throughout the review and analysis of the relevant studies.

Keywords: Aviation, airside operations, meta-heuristics, literature review, classification framework

1. Introduction

Due to the rapid growth of worldwide air transport demand, various airports have experienced airport congestion and disruption of planned schedules. Congestion pricing has been proposed by economists in order to optimise the scarce airport resources [1, 2]. For example, airport authorities charge airlines higher parking fees for landing, using gate slots or aircraft stands at airports during peak hours. However, such pricing mechanism has only small or no effect on reducing the wastage associated with airport traffic congestion or enhancing facility utilisation socially [3]. Airlines will transfer the associated congestion costs to the customer by raising the price of air tickets due to the low cross-elasticity of demand between peak and off-peak periods for air travellers [4]. Current literature realises that congestion pricing may not be able to resolve the airport congestion when air traffic is dominated by a few airlines with greater market power [5-7]. To increase the throughput of air transport and be capable of handling disruptions in airports, capacity expansion at busy airports is inevitable. However, it may not be feasible to construct new runways, flight slots, and remote terminals because of political, environmental, geological, and economic constraints [8]. Alternatively, the short-term solution is to reduce airport congestion and enhance airport facilities usage by utilising the available resources at airports. It is worth noting that the advancement of computer science and mathematical optimisation has contributed to the development of the aviation industry. Various engineering applications have been proposed for optimising airport capability to handle air transport; ensuring safety during flight and navigation; controlling the load balance of runway and airport infrastructure.

In the late 20th century, exact methods in Operations Research, such as Linear Programming and Branch-and-Bound, have played a key role in improving decision-making and efficiency, which attempt to arrive at an optimal level of real-world mathematical models, particularly in industrial engineering and operations management. It is remarkable that more than a thousand of operations research scholars and engineering applications in the aviation industry strive to sustain a high level of service; improve the robustness of scheduling and minimise the total tardiness of all flights and related activities with tight constraints, except the lengthy CPU time in reaching an optimal solution. In computational complexity theory, a large instance for Non-deterministic Polynomial-time hard (NP-hard) problems seems to be implausible to achieve the optimal solution in polynomial time, assuming that $\mathrm{P} \neq \mathrm{NP}$. Moreover, a significant computational effort is required to resolve complex, high-dimensional and NP-hard problems under uncertainty [9].

In this regard, the research focus has shifted to heuristic and meta-heuristic approaches after the 20th century. Due to the slow convergence rate to optimise a large size NP-hard problem with exact algorithms in practice, a considerable number of airside operations research projects using heuristics and meta-heuristics can be traced in the current literature from small instances to higher-order, complex and stochastic combinatorial problem, or even real-life CO applications [10]. Heuristics is regarded as basic approximate algorithms for providing near optimal results [9, 11]. However, the design of heuristics is problem-specific and problem-dependent methods. Meta-heuristics approach is a high-level problem-independent framework, which provides a trajectory of searching for close-to-optimal solutions from practical problems within satisfactory computation time [9, 12]. The design of a meta-heuristic algorithm includes two major concepts, which is exploitation and exploration. Exploitation refers to the ability of foraging around a promising candidate solution to reach the optimal solution, while exploration indicates the ability of terminating searching under the condition of local optimal trapping [13]. The selection of proper meta-heuristics was related to the complexities of exploitation and exploration on the CO problem.

In general, meta-heuristics can be categorised as the single solution-based methods and population-based methods [14]. The single agent-based methods also called trajectory methods, by constructing a searching process regarding an individual solution. The trajectory methods include, but are not limited to Tabu Search [12], Greedy Search [15] and Iterative Local Search [16] algorithms. The existing population-based algorithms fall into three major categories: Evolutionary Algorithm (EA), physics-based algorithms and Swarm Intelligence. The typical examples of EAs involve the Genetic Algorithm (GA) [17], Memetic Algorithm [18] and

Differential Evolution algorithm [19]. EAs deal with information exchange procedures among several candidates by continuously improving the solution quality by iterations, which are known as a blind search method that seldom exploits the domain knowledge and uses evolutionary operators iteratively from known solutions [20]. The simple mechanism of evolutionary operators can be effective in exploitation phase, but the balance of exploration and exploitation is often ignored in the design of the algorithms. By contrast, many naturally inspired meta-heuristic algorithms, including physics-based and SI-based algorithms, have gained increasing popularity because of their high efficiency, which involves specific controlling parameters to maintain the balance between exploitation and exploration. The physics-based meta-heuristics approach is a kind of discipline that aims to simulate the laws of natural science and knowledge of nature in algorithm design. The search agents perform searching according to the natural interaction between matter and energy. Despite the fact that the control parameters usually contain complex functions that lead to long computation time, certain physics-based algorithms are promising in achieving optimal or near-optimal solutions [21]. Representative examples are Big-Bang and Big-Crunch algorithm [22], Gravitational Search Algorithm [23], Ray Optimisation algorithm [24]. Swarm intelligence (SI) is a new type of bio-inspired meta-heuristics that emphasises distributing individual agents for solving hard CO problems. The philosophy of SI, which incorporates the collective behaviour of natural species, is a fascinating meta-heuristics research area in the contemporary evolutionary computation. Although SI for optimisation is still in the proof-of-concept stage in industrial engineering, current publications recommend that SI is qualified to obtain good-quality solutions than single-based and evolutionary methods given a reasonable CPU time. Compared with physics-based algorithms, SI-based algorithms highlight the simple collective behaviour of individual agents rather than complex controlling mechanisms. During the era of SI, different SI-based algorithms have been introduced to CO applications such as the Artificial Bee Colony (ABC) algorithm [25], Ant Colony Optimisation (ACO) algorithm [26], Bat algorithm [27] and Particle Swarm Optimisation (PSO) [28].

1.1. Contribution of the research

A large amount of meta-heuristics with different features and intrinsic characteristics have been proposed throughout the last four decades and found to be a promising technique for real-life application. The availability of periodic review and assessment becomes more important to guide the readers in understanding the meta-heuristics research progress and highlight the research potential in the domain of the airside operations system with a meta-heuristics approach. The comparison of the meta-heuristics techniques in airside operations research is crucial so as to explore the future research direction. Hence, this paper attempts to identify the concealed research field of meta-heuristics research in airport operation.

1.2. Organisation of the paper

The organisation of this paper is summarised as follows. After the background of the airside operations research and meta-heuristics in **Section 1**, **section 2** presents the review framework and the selection criteria of the relevant articles. **Section 3** summaries the classification and description of the meta-heuristics (See **Section 3.1**) and the research findings of operations research in airside activities (See **Section 3.2**). The statistical analysis of the studies are reported in **Section 4**. The trend analysis and the research potential of the field are illustrated in **Section 5**. Finally, the concluding remarks are raised in **Section 6**.

2. Research methodology

The primary objective of this paper is to present a taxonomic framework for outlining and consolidating the current research field of extant airside operations in the literature with reference to functionality, which indicates potential topics for future research and development in the aviation industry. The literature review approach necessarily contributes to the research progress to discover potential research and study in airport OR, which is a valid tool to synthesise and consolidate scattered knowledge systematically [29]. In **Fig. 1**, the review process of this review article follows the four major steps proposed by Mayring for conducting content analysis [30].

Fig. 1. Research process of a structuring content analysis [30]

An initial search from the *Google Scholar* recommended an enormous number of publications related to “aviation”, since there are insufficient works on reviewing the combined research on airside operations research and meta-heuristics. After a pre-screening process, certain keywords were found from the abstract and introduction. Those keywords were referred to the delimitation of the selected publications in order to extract the most relevant and renowned publications. The publication search for specific journal articles was conducted using a keyword search of the electronic library database. The literature review was mainly conducted from the electronic library, such as *IEEE Xplore Digital Library*, *ScienceDirect-Elsevier*, *Springer Online Journal Collection*, *INFORMS PubsOnline* and *Emerald Insight*. Supplementary journal publications were also explored from the *Google Scholar* database. The targeted publications should mainly constitute functional-level CO models, including aircraft scheduling, gate assignment problem (GAP), air route network (ARN), airport taxiway optimisation. The search terms were also derived from the review articles of operation search in aviation or Air Transport Management (ATM), and the taxonomic review of meta-heuristics. The criteria for selecting relevant publications are specified as follows. The review process was restricted to the interdisciplinary research of the meta-heuristics and airside OR. Only peer-reviewed relevant journals written in English were selected. We delimited the primary studies following the inclusion and exclusion criteria as shown as follows.

Inclusion criteria are:

(i) Operations research using meta-heuristics for airside activities
(ii) Deterministic, dynamic, stochastic and robust modelling for airside activities
(iii) Journal articles with impact factors in recent years
(iv) At least proposed one meta-heuristic(s) in the research methodology

Exclusion criteria are:

(i) Non-operations research using meta-heuristics for the airside activities
(ii) Review articles, conference papers and book chapters
(iii) Research methodology with non-meta-heuristics but using meta-heuristics as benchmark for comparison

According to the above inclusion and exclusion criteria, 103 studies were extracted for the formulation of the taxonomy framework in airside activities using meta-heuristic approaches and the analysis of the trends in the research domain.

3. Problem classification

3.1. Classification scheme of meta-heuristics

The solution methods for airside operations research can be categorised into two major groups, which are exact approach and approximate approach. Although the exact approaches are the frequent approaches to optimise CO models, it lacks the capability to handle practical cases within a reasonable time frame. The approximate approach, especially meta-heuristics, has become more favoured for searching for a good solution with a reasonable computation time. The approximate approach can be further divided into heuristics and meta-heuristics methods. The concept of the meta-heuristics was introduced by [12], aiming to encounter the problem of local optimum through the controlling mechanism during the recursive search method. The fundamental controlling mechanism in the meta-heuristics consists of trajectory method, control and memories, hybrid strategies, parallelism, and decompositions [31]. Many researchers are working on improving the solution quality as well as the computational effort of the meta-heuristics, according to the above control aspects. Therefore, various meta-heuristics algorithms have been proposed for different engineering theories or applications. Another remarkable feature in meta-heuristics is to maintain a reasonable adjustment between exploitation and exploration during the search, which leads to better solution quality among the population at each iteration. The classification of meta-heuristics depends upon the feature and working mechanism of the meta-heuristics, including single-solution meta-heuristics, biological evolution, physics-based algorithms and swarm intelligence, as shown in **Fig. 2**.

Fig. 2. Classification of optimisation techniques

3.1.1. Single-solution meta-heuristics

The mechanism of determining a near-optimal solution and defeating local optimal traps relies on the use of stochastic operators for strengthening the search performance of the meta-heuristics and exploiting better solutions from the prior knowledge [32]. The search method in the single-solution meta-heuristics performs a trajectory search with a single solution iteratively from a known solution. The current solution will be replaced when an improved solution with a superior objective value is found during the exploitation process. It is straightforward to see that the single-solution meta-heuristics provide an efficient exploitation at each iteration in approaching the local optima, but the solution may not be a global optimum [33]. In order to overcome the convergence problem, the methods of searching between neighbourhood structure and memory-based searching are the conventional approaches to maintain diversification in a trajectory search [31]. The examples of single-solution meta-heuristics are shown in **Appendix B** (See. **Table 14**).

3.1.2. Biological evolution

Biological evolution is another group of meta-heuristics that utilises the performance of the population solution. The centre of the searching in biological evolution focuses on the hereditary through genetic information or ancestral memories from a group of candidate solutions [17]. The mechanism in biological evolution relies on natural selection and genetic variation. The process of the natural selection allows evolutionary changes of maintaining certain traits in a population to adapt to the environment, while genetic variation is the process by which an individual becomes better suited to the living environment than other individuals. The examples of biological evolution are illustrated in **Appendix B** (See. **Table 15**). The review on biological evolution was presented in Kumar et al. [34] and Weile and Michielssen [35].

3.1.3. Physics-based algorithms

Physics-based algorithms represent an optimisation technique using the natural practice of physical and chemical discipline, including quantum theory, electrostatics, Newton's gravitational law, and the laws of motion. Various physics-based algorithms have been proposed in recent years [36]. A typical example of the physics-based algorithms is Simulated Annealing, which imitates heat treatment in metallurgy and material science. The examples of the physics-based algorithms are presented in **Appendix B** (See. **Table 16**). The architectures of physics-based algorithms were described in Biswas et al. [37] and Can and Alatas [36].

3.1.4. Swarm intelligence

SI-based algorithms perform effectively and efficiently to explore and exploit the searching progress that becomes more and more favourable to resolve sophisticated CO models [38]. Even though there are numerous SI-based algorithms, the design of algorithms still follows three main features: (1) Decentralisation implies that no central control mechanism is involved. This arrangement enhances the robustness of searching for the optimal solution when the algorithm is dealing with a large-size CO problem. The behaviour of individuals is determined by itself without order and command from the centre to reduce the controller-and-back communication [39]. (2) The essence of self-organising in SI is able to balance the exploitation and exploration processes through trial-and-error interactions. In addition, self-organisation works as an “invisible hand” by individuals’ efforts to pursue a socially desirable outcome or goal through self-organising behaviour, which allows any separated individuals back on track ultimately, such as positive feedback, negative feedback, fluctuations and multiple interactions [40]. Self-organisation allows interactions between individuals to exchange information with simple operations that contain arbitrary rules, that reinforces the exploration during searching and sometimes allows the certain failures of individuals’ performance [39]. (3) Collective behaviour refers to the coordinated efforts of all individuals to accomplish the global goal desired from the model. The composition of the three main features in SI contributes to the success of robust searching. The examples and search methods of SI algorithms are shown in **Appendix B** (See. **Table 17**). We suggested a review article on the evaluation of algorithmic architectures of swarm intelligence [41].

3.1.5. Hybrid meta-heuristics

Modification approaches are still the dominant methods to improve the solution quality. In general, high-level meta-heuristics approaches are more favourable in solving complex multiple-objective CO problems. Improving the solution quality and computation time are the primary goals in the development of the meta-heuristics. According to the complexity of identifying the search regions and the possibility of being trapped in local optima, algorithm customisation is the general approach to maintain a balance and allow interaction between diversification and intensification. The balance between diversification and intensification can be viewed as the exploitation of a promising region or local optimal solution and exploration of an optimal global solution among the searching space. Depending on the complexity feature of CO problems, modification of the original meta-heuristics is necessary to match the model’s specific properties. The hybridisation can be completed through a two-stage approach or one meta-heuristic guiding another meta-heuristic. The phenomenon of premature convergence normally existed in conventional population-based algorithms. The design of previous population-based algorithms lacked the capacity to maintain diversity between a set of solutions, namely diversity loss. A possible improvement could be integrated with another neighbourhood centre search algorithm or intensity-based algorithm to enhance the exploitation ability of the population-based algorithm, some of which are: GA with ACO [42] and MA with ACO [43] for ASSP. Much effort has been recently made regarding hybridisation using two neighbourhood search algorithms for AGSS, ASSP and AGAP models, such as Variable Neighbourhood Descent (VND) with LNS [44], VND with SA [45], and SA with TS [46, 47].

3.2. Classification scheme of airside operations research

The design of air transport planning and management is a multiple-level, collaborative operation to make daily or periodic decisions in the aviation sector. Airlines, airport authorities, air transport practitioners, and agents are involved in air transport planning and management. Most of the airside operations research in the literature can be formulated as CO models, which can be summarised as follows: (1) Job Shop Scheduling Problem (JSSP), (2) Travelling Salesman Problem (TSP), (3) Vehicle Routing Problem (VRP) and (4) Quadratic Assignment Problem (QAP). JSSP, TSP, VRP and QAP have been proven to be Non-deterministic Polynomial-time Hard (NP-hard) Problem [48-51]. Airside OR, in general, concerns collaborative and cooperative approaches associated with various entities to perform integrated optimisation CO modelling with multiple objectives to improve the operation efficiency under budget constraints.

Most air traffic operations research is directly initiated from actual requirements and regulation by the civil aviation administration. The separation time between aircraft en-route or surface traffic operation is the typical constraint for safety reasons in airside OR. For example, the safety en-route distance between adjacent flights is strictly supervised by an en-route control centre via the visual aid of a two- or three-dimensional radar screen. Besides, operational efficiency and customer satisfaction are linked to the measurement of the performance of airside OR. Stand allocation under congested airport gate occupation is an interesting research direction, which synthesises the operation of aircraft landing schedules and gate assignment to reduce the time for holding procedures and resolve traffic in the terminal airspace area. The objectives of the airside operations research model can be summed up in four major aspects: safety, economic, customer satisfaction and operational efficiency. In addition, certain research papers have introduced environmental control measurement of air pollutants and greenhouse gases. **Fig. 3** described the sub-criteria of each research objectives in the field.

Fig. 3. The research perspective in the airside operations research

The implementation of airside operations research comprises various activities and operations. **Fig. 4** presented the essential elements and their correlation in airside operations. With regard to our proposed taxonomic framework after our comprehensive literature review, the articles were differentiated into three major categories, namely Airspace and Air Traffic Flow Management (ATFM), Aircraft Operations in Terminal Manoeuvring Area (AO in TMA) and Surface Traffic Operation (STO). The sub-dimensions of airside operations research are presented in **Fig. 5**.

Fig. 4. Schematic diagram of the airside operations research

Fig. 5. Taxonomy of airside information system

3.2.1. Airspace and air traffic flow management

Future airspace capacity is expected to increase and require high development of en-route traffic control in order to maintain high volumes of air traffic and conflict-free program and create flexible flight paths for varying demand patterns, as shown in **Fig. 6**. The worldwide airspace has become complicated and more challenging to manage. Particular emphasis in Air Traffic Flow Management (ATFM) is placed on efficiency and flight conflict resolution in flight path problems due to uncertain weather in airspaces, restricted regional airspace regulations, and overwhelming traffic demand recently. Advancement in navigation technology and computation intelligence is becoming a radical approach to enhance airspace capacity and flow program efficiency.

Fig. 6. Schematic diagram of the airspace and air traffic flow management

3.2.1.1. Aircraft avoidance

Table 1 summarises the research on meta-heuristic approaches for aircraft collision avoidance. Aircraft collision avoidance is an important aspect of airspace safety navigating systems. With the deployment of Global Navigation Satellite Systems, various prediction and prevention collision avoidance systems have already been developed to offer pilots traffic alerts and avoidance suggestions. The Traffic Collision Avoidance System is an airborne system design, which can be classified on the basis of functionalities, such as visualisation for airspace navigation, conflict detection in the nearby vicinity and possible confliction advisory [52]. Considering the 2D trajectory planning, Guan et al. [53] presented an improved MA in order to enhance the solution quality based on the work conducted by Alam et al. [54]. Alonso-Ayuso et al. [55] suggested a decision support system together with the VNS algorithm for the TCAS by means of changing aircraft directions. To achieve a higher level of applicability, 3D trajectory planning was proposed. Dougui et al. [56] introduced a new nature-inspired algorithm, entitled Light Propagation algorithm, to resolve conflict-free fourth-dimensional trajectory problems. In order to manage a large-scale TCAS, the dynamic grouping strategy was suggested to reduce the computational burden via a variance-priority-based group [53]. Chaimatanan et al. [57] conducted a trajectory-based collision avoidance with an AFP approach to minimise the number of interactions between aircraft by the GA.

3.2.1.2. Flight path optimisation

Table 2 presents the application of Flight Path Optimisation (FPO) using meta-heuristics, which can be shown that Biological Evolution is the majority of the research methodology in the field. FPO can be considered as an aircraft routing network in multiple-dimensional flight trajectory composed of points and edges. The current approach is to define the flight path ahead of time. Worldwide air transport has reached the ceiling of airspace capacity, and various airports have experienced flight delays and low operational efficiency due to airspace congestion. Ground Delay Program (GDP) is a common approach to manage flight re-scheduling under inclement en-route or terminal weather, en-route traffic and flight incidents. The implementation of GDP maintains free flow of air traffic volume in a period, which allows the airports to absorb airborne delay time and moderate the probability of reaching the maximum quantum of airspace traffic [58]. Abdelghany et al. [59] argued that GDP may lead to operational inefficiency and airport congestion, which can be resolved by an online ARN approach, including Crossing Waypoints Location (CWL) optimisation and AFP. The major objective of CWL optimisation is to reroute current flights along different airborne paths. [60]. Hu et al. [61] introduced a real-time CWL optimisation based on improved GA for the current structured airspace. Zhang et al. [62] conducted large-scale multiple objectives CWL optimisation in the French airspace. Guan et al. [63] compared their proposed algorithm with several meta-heuristics for detecting congested airspace.

Airspace capacity in the CWL optimisation model is limited, as it is bounded by the restricted number of routes and nodes. The relaxation of certain routes is demanding, but the expansion of ARN is regulated by civil aviation. Airspace Flow Program (AFP) is the new paradigm to control the traffic flow based on the available airspace capacity to make conflict-free airspace discrete for FPO. The proposed AFP is to minimise the anticipated negative impacts, such as aircraft collision, carbon emissions and operational costs, while allowing certain control by pilots to perform conflict-free re-routing using the Air Navigation System without consulting the Area Control Centres [61]. The flight path from the two connected nodes is defined as a time-slice flight path, which gives more alternatives to solving flight collision and optimising flight trajectory [61]. Abdelghany, Abdelghany and Niznik [59] additionally conducted a two-phase heuristic to optimise the AFP using the basic GA. In their experiment, the first-phase heuristic is able to screen out infeasible solutions, and pass the feasible intermediated solution to further optimise with less computational effort. Blasi et al. [64] presented a sampling density threshold PSO to avoid the particles crowding problem for a 2-dimensional flight trajectory optimisation which can denote non-circular and concave obstacles taking into account the flight dynamic.

Table 1

Research on meta-heuristics for airspace and air traffic flow management - aircraft collision avoidance

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
2D trajectory plan	Single solution-based meta-heuristics	Neighbourhood structure	2015	VNS	Exact method[#]; Sequential Integer Linear Optimisation (SILO)	Min. interaction between trajectories	[55]
	Physics-based algorithms	Gene	2014	MA with local search operators (type-G; type-A; type-M)	GA; Cooperative co-evolution with a random grouping (CCRG) heuristic	Min. the flight delays; min. the number of conflicts	[53]
3D trajectory plan	Biological evolution	Gene	2009	GA	N/A	Min. the number of missed detects and false alarms	[54]
			2011	Efficient Genetic Webs	N/A	Min. fuel consumption of all flights	[65]
	Physical-based algorithms	Electromagnetic radiation	2013	LPA	GA; Triangle mesh algorithm [66]	Min. the interaction between trajectories	[56]
		Energy	2014	SA with hill-climbing local search strategies	Exact method	Min. the interaction between trajectories	[57]

[#]: solved by *IBM ILOG CPLEX* Optimisation Studio

Table 2

Research on meta-heuristics for airspace and air traffic flow management - flight path optimisation

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
Airspace flow program	Swarm intelligence	Particle	2013	PSO	N/A	Min. the flight path length	[64]
Airspace flow program / crossing waypoints location problem	Biological evolution	Gene	2004	GA with heuristic rules	Variants of the proposed algorithm	Min. the flight path length	[61]
Crossing waypoints location problem	Biological evolution	Gene	2007	GA	Exact method; Two-stage heuristic	Min. the cost of flights cancellation and late arrival	[59]
			2012	MA with pull-push operator	NSGA-II; MOEA based on decomposition; Comprehensive PSO	Min. the number of conflicts; min. the total airline cost	[67]
		Species	2015	Multi-island PEA	MOGA; MOEA based on decomposition	Min. the airspace congestion; min. the extra delay costs	[63]
			2015	Multi-island PEA with constant/random migration interval	NSGA-II; MOGA; MOEA based on decomposition; CC-based heuristic [62]	Min. the total delays; min. the total workload	[62]
Multi-airport capacity management	Biological evolution	Gene	2007	GA with receding horizon	GA; Exact method with receding horizon	Min. the delays by redirect flights between airport	[68]

[#]: solved by *IBM ILOG CPLEX* Optimisation Studio

3.2.2. Aircraft operation in terminal manoeuvring area

The objective of Traffic Management in a Terminal Manoeuvring Area / Terminal Manoeuvring Centre (TMA/TMC) is to maintain a vital balance between smooth air traffic flow and the capacity of surface traffic operation in an airport. A TMA deals with airport capacity management, safe operation of all the flights and efficient allocation of airport resources. Two major operations are considered in this category: airline schedule recovery and disruption-tolerant sequencing during aircraft landing and take-off, described in **Fig. 7**. Due to the multi-objective and stochastic nature of airport operations, the applications of meta-heuristics work as an expert system and support the Air Traffic Control (ATC) controllers in their decision-making to provide high-quality solutions.

Fig. 7. Schematic diagram of aircraft operation in terminal manoeuvring areas

3.2.2.1. Aircraft scheduling and sequencing problem

ASSPs are one of the important aspects of ATM, which considers the traffic of air transport and the landing and take-off sequences. Matching between aircraft sequencing and selection of runways can also be considered as a ASSP model. It consists of two major operations: Aircraft Landing Problem (ALP) and Aircraft Take-off Problem (ATP) with single or multiple runways. **Table 3** summarised the classification and solution approaches using meta-heuristics in ASSP model. The conventional ASSP/ALP/ATP models apply the First-Come-First-Served (FCFS) approach to arrange aircraft landing or take-off sequences based on the order appearing on the radar system. Maximum Position Shifting refers to the maximum allowance for aircraft shifting forward or downward from the position in the FCFS sequence, while relative position shifting defines the maximum threshold for aircraft shifting from the previously re-arranged sequence. Beasley et al. [69] argued that maximum Position Shifting for the FCFS approach causes inefficiency in ALP, although the FCFS sequence is the most popular scheduling approach across the world. Separation times between two consecutive flights are dynamic during the operation. Relative position shifting is a novel approach, which allows flexibility in rearranging ASSPs. Moreover, aircraft generate wake vortices as a natural consequence of lifting, which can put the following adjacent aircraft at risk [70]. Therefore, a set of hard constraints of safety distance and time separation during landing and take-off sequencing must be confirmed except in cases of emergency. The minimum safe distance metric provided the basic idea of safe landing requirement of successive landings [69]. Pinol and Beasley [71] first presented SS and the Bionomic algorithm for the ALP model with a time window to resolve a large instance with 500 aircraft and five runways within a minute. Bencheikh, Boukachour, Alaoui and Khoukhi [42] formulated the ALP as a JSSP model to handle large size instances, ranging from 100 to 500 aircraft. Salehipour, Modarres and Moslemi Naeni [45] integrated SA with VND and VNS for ALP problems. Ng and Lee [72] further modified the VNS algorithm in Salehipour, Modarres and Moslemi Naeni [45]'s work. The results obtained are generally the same as the result from *CPLEX* but with a short computation time.

GA is still a dominant approach to handle the complex models, such as the multi-objective or dynamic ASSP model. Dastgerdi et al. [73] introduced a new EA approach for solving the congested single runway airports. Mokhtarimousavi et al. [74] adopted a Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to resolve the multi-objective ALP model. Bencheikh, Boukachour and Alaoui [43] also raised a dynamic ALP model solved by an integrated MA and ACO algorithm. Alternatively, solution quality in the ALP model can be enhanced by incorporating with a Receding Horizon Control strategy. Hu and Chen [75] first attempted to introduce the RHC strategy to solve the dynamic ALP problem and reduce the computational effort for the GA. Besides, swarm intelligence for ALP model has been studied [76, 77]. Ng et al. [78] enhanced the convergence of ABC algorithm and developed a robust optimisation for ASSP using mixed-mode runway operation in hedging arrival and departure uncertainties.

3.2.2.2. Airline fleet schedule planning

An overview of FSP articles using meta-heuristics is given in **Table 4**. We suggested a review articles on the airline scheduling problem [79]. Airline scheduling is generally established one season ahead of the actual operation in accordance with the forecast of air transport demand and the consideration of the seasonal and growth rate factors taken into account. Other resources can afterwards be settled, such as fleet assignment, maintenance routing, crew scheduling and recovery planning for disruption. The design of initial airline schedules must be planned ahead to avoid disruption and compile in light of practical usage, legislation by the airport authorities, and time allowance for buffering. Andersson [80] introduced a TS with path rethinking for the Flight Perturbation Problem model to restore the original schedules when the unexpected events occurred. The extended version of the multi-objective Flight Perturbation Problem model for short-haul flights focuses on improving the turnaround rate of short-haul flights [8, 81, 82].

Achieving sub-optimal solutions in decomposed decision-making does not guarantee reliable and flexible airline recovery since the set of sub-problems is interconnected and not independent. Thus, an aggregate approach has been proposed in airline recovery management. The main goal of airline scheduling is to ensure that operations can be performed on time with no or slight effect on an airline's tardiness or interruption to airport ground operations. Performing upstream integration is fairly reliable to build a robust airline schedule and mitigate the possibility of the reassignment. Zegordi and Jafari [83] included the consequence of disrupted operation as part of the objective function by minimising the impact on the propagation of disruptions using ACO. Apart from the single recovery model, integrated aircraft and passenger recovery approaches are regularly adopted to minimise the cost incurred in passenger reservations and operating cost during a flight disruption, flight cancellation, and airport congestion [84].

Table 3

Research on meta-heuristics for aircraft operation in terminal manoeuvring area – aircraft sequencing and scheduling problem

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
Aircraft landing problem	Single-solution meta-heuristic	Neighbourhood structure	2014	Adaptive LNS	SS [71]; SA + VNS [45]	Min. the average penalties (earliness and lateness)	[85]
			2015	ILS with multiple perturbation operators	Variants of ILS	Min. the total penalties (earliness and lateness)	[86]
	Biological evolution	Gene	2001	GA with local search	GA	Min. the squared deviation of the scheduled and actual landing time	[69]
			2004	GA	FCFS; Cheapest insertion heuristic [49]	Min. the weighted total delay cost	[87]
			2004	GA	N/A	Min. the total airborne delays	[88]
			2005	Permutation-representation GA with receding horizon	GA [49]; Conventional TSP	Min. the total airborne delays	[75]
			2006	SS; Bionomic Algorithm	FCFS	Min. the squared deviation of the scheduled and actual landing time; min. the total penalties (earliness and lateness)	[71]
			2007	GA with uniform crossover	GA; GA with crossover	Min. the total airborne delay	[89]
			2008	Binary Representation GA	DTSPM [49]; Permutation-representation GA [75]	Min. the total airborne delay in each rolling horizon	[90]
			2011	GLS	GA [91]; SS [88]; Bionomic Algorithm [71]	Min. the squared deviation of the scheduled and actual landing time; min. the total penalties (earliness and lateness)	[8]
			2016	GA with weighted fitness value	GA	Min. the squared deviation of the scheduled and actual landing time; min. the total penalties (earliness and lateness)	[92]
	Physics-based algorithm	Mass	2016	GSA	GA [88]; GA with uniform crossover [93]; SS [71]; GLS [8]	Min. the deviation of scheduled and actual landing time	[94]
	Swarm intelligence	Ant	2010	Efficient ACO with rolling horizon	FCFS; Binary-representation GA[90] ACO	Min. the total airborne delay in each rolling horizon	[95]
			2017	Efficient ACO	Exact method$^{\#}$; Approximation algorithm [96]; ACO; FCFS	Min. the makespan	[97]
		Bat	2013	BA with local search	Bionomic algorithm [71]; SS [71]; Improved ACO [98]; heuristic [99]; FCFS [71]	Min. the deviation of scheduled and actual landing time	[100]
		Particle	2016	PSO with rolling horizon	Exact method$^{\#}$; SA + VND [45]; SA + VNS[45]	Min. the total penalties (earliness and lateness)	[101]
	Hybrid meta-heuristic	Integrated	2013	SA + VND; SA + VNS	Exact method$^{\#}$; SS [71]	Min. the total penalties (earliness and lateness)	[45]
Aircraft	Single solution	Neighbourhood	2013	Meta-RaPS	SA with different greedy	Min. the weighted tardiness	[102]

sequencing and scheduling problem	meta-heuristics	structure			strategies; Meta-RaPS with different greedy strategies		
	Biological evolution	Gene	2014	GA	FCFS	Max. throughput of the runways	[103]
	Physics-based algorithm	Energy	2017	SA	Exact method#; Bionomic algorithm [71]; SA + VND [45]; SA + VNS [45]; SS [45]	Min. the weighted total delay cost	[104]
	Swarm intelligence	Ant	2014	ACO	N/A	Min. the average flight delay cost of each airline; min. the total delay cost	[105]
		Bee	2017	Efficient ABC algorithm	Exact method#; GLS; ABC; Modified ABC; Hybrid ABC with GA	Min. the maximum regret value with regards to the makespan deviation for all worst-case scenarios	[78]
Aircraft take-off problem	Single solution meta-heuristics	Memory structure	2017	TS	FSFC; manual method; seven-aircraft exhaustive heuristic	Min the calculated time of take-off; min. the additional penalty cost; min. the reordering cost; min. the weighted total delays	[93]
Terminal traffic flow modelling	Single solution meta-heuristic	Memory structure	2014	MIP-based TS	FCFS; exact method#	Min. the delay propagation	[106]
		Neighbourhood structure	2017	VNS with delayed job neighborhood operator	TS [106]; centralised meta-heuristic [106]; rolling horizon meta-heuristic [106]	Min. the makespan of the whole traffic flow network	[107]

#: solved by *IBM ILOG CPLEX* Optimisation Studio

Table 4

Research on meta-heuristics for aircraft operation in terminal manoeuvring area – fleet schedule planning

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
Airline schedule recovery	Single solution meta-heuristic	Memory structure	2006	TS with path relinking	Exact method$^{\#}$	Min. the negative consequences of disturbance	[80]
		Neighbourhood structure	1997	GRASP algorithm	N/A	Min. the flight cancellation and delay cost	[108]
			2015	LNS	SimLoop method	Min. the total passenger delays	[109]
			2017	LNS with CNS heuristic	Binary search minimum cost flow algorithm (BSCF)	Min. the flight delay cost; min. the maximal flight delay time; min. the number of flight reassignment	[110]
	Biological evolution	Gene	2008	MOGA	N/A	Min. the number of flight swap; min. the time for flight connection and ground-turn-a-round time; min. the total flight delay time	[81]
			2010	MOGA with hybrid adaptive evaluation vector	MOGA [81]	Min the number of flight swap; min. the number of long-delayed flight over 30 mins.; min. the total flight delay time	[111]
			2010	MOMA	Comparison between biased and randomised selection of the local search operators	Ensure feasibility of the schedule; maintain flexibility of a schedule; min. the stochastic influences in its operating environment	[112]
	Swarm intelligence	Cat	2012	Enhanced PCSO	PCSO [113]; PSO-LDIW [114]; PSO-CREV [114]; GCPSO [114]; MPSO-TVAC [114]; CPSO-H_6 [114]; PSO-DVM [114]	Min. the number of flight swap; min. the total flight delay time; min. the variance of delayed time	[82]
Airline scheduling	Swarm intelligence	Particle	2016	PSO	N/A	Min. penalties induced by flights connections, idle time, buffer time	[115]
Airline scheduling and crew-pairing problem	Biological evolution	Gene	2013	Self-adaptive GA	GA	Max. the total income of the airlines	[116]
Crew recovery	Biological evolution	Gene	2005	GA with mixed crossover	GA; GA with row-based crossover; GA with column-based crossover	Min. the total operational cost	[117]
Crew-pairing problem	Single solution meta-heuristic	Memory structure	1999	Run-ejection algorithm; tabu-crew algorithm	Run-cutting algorithm	Min. the number of crew duties	[118]
		Neighbourhood structure	2015	LNS with polishing method	LNS	Min. the total crew assignment cost	[119]
	Biological evolution	Gene	1996	GA with local search	Exact method$^{\%}$	Min. the total crew assignment problem	[120]
			2001	Steady-state GA	GA based on Chvatal's heuristic [15]; Back's heuristic [121]; GA	Max. the balance of workloads between crews; max. the crew time utilisation;	[123]

					[122]; greedy algorithm	min. the number of crews	
			2013	GA with knowledge-based random algorithm	Column generation; column generation with knowledge-based random algorithm	Min. the total crew assignment cost	[124]
			2013	NSGA-II	Manual method	Min. the delay variance; min. the number of delayed flights; min. the number of duty swap; min. the number of long-delay flights	[125]
	Physics-based algorithm	Energy	1999	SA with local search	Comparison of different strategies of SAs (Singleton, linear Chainer, Steepest Desent)	Min. the total crew assignment cost	[126]
			2007	SA	Manual method; TS; GA	Min. the average deviation of actual and planned crew-pairing roster	[127]
	Swarm intelligence	Ant	2011	ACO with heuristic	GA	Min. the total crew assignment cost	[128]
		Particle	2013	PSO with local search	PSO; GA; ACO	Min. the total crew assignment cost	[129]
Fleet schedule recovery (integrated airline and crew-pairing recovery)	Single solution meta-heuristics	Neighbourhood structure	2014	Improved LNS	Compared the score from the competition	Min. the penalties induced by flights connections (e.g. idle time and buffer time)	[84]
	Biological evolution	Gene	2017	MOGA	Inequality-based MOGA [130]	Max. the number of free crews; min. the extra cost; min. the flight duty period; min. the standard deviation of the flight time assigned to the crews	[131]
Fleet schedule recovery (integrated airline and passenger recovery)	Single solution meta-heuristics	Neighbourhood structure	2011	LNS	Score from the competition	Min. the penalties induced by flight connections (e.g. idle time and buffer time)	[132]
			2016	Two stage model with GRASP algorithm and local search heuristic	Manual method; Separate Recovery Method (SRM)	Min. the reassignment cost; min. the refund cost of passengers; min. the total delay cost	[133]
	Biological evolution	Gene	2009	GA with legality repair heuristic	GA with random feasibility repair heuristic; GA with improved feasibility repair heuristic	Max. the balance of workloads between crews; max. the crew time utilisation; min. the total assignment cost	[134]

$^{\#}$: solved by *IBM ILOG CPLEX* Optimisation Studio; $^{\%}$:solved by lp_solver optimisation tool

3.2.3. Surface traffic operation

Inefficiencies in surface traffic operations cause significant financial loss and impact to other airport operations and customer satisfaction. Such delay and airport congestion is sensitively dependent on previous postponed and disrupted schedules. Any disrupted airport users have large effects and further contributed to operation inefficiency, running costs of the airline, and environmental problems in a busy airport specifically, which can result in large variations compared with planned schedules [135]. Scheduled flights may require push back and being put on hold in the corresponding slot, which creates unnecessary carbon emissions, fuel usage, and pollution due to suspension. Managing all ground operations by a single ground-controlling agent is impracticable. To address the shortcoming of performing the global optimum in surface traffic operations, scholars have focused on optimising the subsidiary operations in surface movement, such as aircraft maintenance and planning, ground handling service movement, taxiway optimisation, and flight gate assignment. The simplified surface traffic operations are shown in **Fig. 8**.

Fig. 8. Schematic diagram of surface traffic operation

3.2.3.1. Aircraft gate assignment problem

The publication in aircraft gate assignment problem using meta-heuristics are summarised in **Table 5**. Apart from the operational and strategic aspect of surface traffic management, the AGAP is another important part regarding customer satisfaction. Minimising passengers' inconvenience, the distance between departure gates and baggage claim area, and passengers' travelling distance between two connecting flights are the most common objectives in the AGAP model. Inefficient AGAP has a rare influence on airport disruption apart from insufficient flight gates provided by an airport. However, it does affect passengers' perceived service quality and perceived value. Bolat [136] proposed a static AGAP model in order to utilise the flight gate usage without the consideration of customer aspects. The AGAP can also be developed as a Clique Partitioning Problem model that can be solved effectively using the EC algorithm by simplification [137]. Cheng, Ho and Kwan [46] proposed a customer-oriented AGAP model, which considered the walking distance for arriving, departing and transferring passengers. The numerical experiment indicated that a hybrid SA with TS outperforms the GA, SA and TS with regard to objective function by sacrificing CPU time.

The Aircraft Gate Reassignment Problem model is the most direct method to recover GAP disruption [138]. On the other hand, the gate reassignment model has several shortcomings. For instance, it merely rearranges the assigned flights. The reassignment further creates a disturbance to planned schedules. In certain cases, the model cannot find any alternatives because of reaching a maximum capacity of airport facilities other than recovery from the abnormal GAP model. Moreover, the input attributes in scheduled arrival and landing are stochastic in nature. Therefore, reassignment may not significantly influence airport recovery. To resolve the above problems, a stochastic GAP model with uncertain parameters by a finite set of scenarios in realistic arrival and departure times of all the flights allows more adaptive and dependent flight gate assignment in real-life application. The proposed stochastic GAP allows certain infeasibility to encounter the problem of conflicting constraints. A robust GAP model with anti-disturbance ability dealing with the uncertainties is another research direction to allocate enough buffer and idle time by sacrificing certain resources [139]. The robustness of the stochastic GAP model does not present a perfect assignment to all scenarios or situations. The possibility of flight perturbation still exists and significantly contributes to airport congestion for any single case. The over-constrained AGAP model with a shortage of available gates presented by Ding, Lim, Rodrigues and Zhu [47] indicated the effect on the above situations. No solutions are feasible under such preference system which resulted from contradictory constraints, which contribute to the aviation academia and provide insight to allow temporary parking and perform remote gate assignments at a busy airport. Guépet et al. [140] further conducted the AGAP work as Stand Allocation Problem.

3.2.3.2. Aircraft maintenance routing problem

Table 6 reviews the maintenance routing problem using meta-heuristic approaches. Periodic aircraft maintenance must be carried out to ensure a high safety level and operational status during flight [141]. Corrective maintenance is undesirable in aviation industries, as any defects or failures found during operations cause adverse effects on safety and reputation, and emergency recovery by assigning a new flight for the disrupted customers. It would seriously lead to causes of death when the aircraft is in operation. Therefore, preventive or predictive maintenance approaches are designed to forecast when the maintenance should be accomplished. The preventive maintenance is to measure the remaining life cycle and minimise the downtime cost. As for aircraft maintenance, the time interval of safety review is not fixed on account of the high wage rate of maintenance workers and tightened time schedules in order to return the aircraft to service. Angus et al. [142] aimed to minimise the total flow time in an Aircraft Maintenance Routing Problem (AMRP) using the GA. Quan et al. [143] proposed an aircraft preventive maintenance schedule with preference-based EA. In this model, Pareto optimal solutions considered the balance of minimising the numbers of workers, makespan and consideration of airline preferences. Başdere and Bilge [144] introduced a weekly-based operational AMRP rather than the few-day-based to minimise the available legal flying time between two consecutive maintenance operations to yield the largest aircraft-in-service usage. Since the solution space is limited to a weekly-based horizon, single solution-based meta-heuristics is more appropriate and preferable regarding CPU time. Conditional-based maintenance is a trend-oriented policy that aims to identify the remaining life of an engineering component. Cost for preventive maintenance could be significantly reduced once the reliability measurement of component health can be accessed via a sensor network. Gerdes [145] suggested that machine learning can assess the health condition of the aerospace components by retrieving historical records and sensory data. Nieto et al. [146] designed an online hybrid PSO model that closely monitors aircraft components and predicts the remaining useful life without any historical inputs.

3.2.3.3. Airport ground service scheduling problem

Table 7 presents the characteristics of airport ground service scheduling (AGSS) using meta-heuristics in the literature. Ground handling services are particularly susceptible to airport disruption. Ground processes are often disrupted due to weather conditions, delay of flight schedules or disturbance of related aircraft turnaround processes. Rescheduling of multiple ground operations is more complex to achieve the global optimal solution due to the stochasticity of travelling time and large number of ground service entities. AGSS can be classified as (1) allocating individual resources to all flights, (2) arranging all the service activities of an individual flight and (3) optimising all the service activities to all flights [147]. Kuster et al. [148] formulated a Resource Constrained Project Scheduling Problem for the third type of AGSS in a practical context. Indeed, computational effort is required when the AGSS system incorporates with a large number of agents. In this regard, Ip et al. [149] divided AGSS into several sub-problems as Vehicle Routing Problem with Time Window to accelerate the convergence speed in an iterative algorithm that satisfies the real-time needs in scheduling using the GA. Padrón, Guimarans, Ramos and Fitouri-Trabelsi [44] also tried to optimise the aircraft turnaround process using ACO for a decomposition schema of AGSS and minimise the waiting time before operations and the overall AGSS completion time.

3.2.3.4. Taxiway optimisation

Meta-heuristics for taxiway optimisation are outlined in **Table 8**. Taxiway optimisation functions as control of aircraft surface movement named Surface Movement, Guidance and Control Systems. Achieving an efficient use of airport operations has gained significant interest recently. The growing air transportation demand creates tension in a TMA in most international airports, which limits the capability to handle aircraft take-off and landing. Specified flow capacity, flight conflicting and flow conservation constraints in four-dimensional trajectory are introduced for Surface Movement, Guidance and Control Systems with regard to the objectives of minimising delay time, the total tardiness of all flights and relaxing the adverse effect on ground units. García et al. [150] introduced the dynamic surface flow management to optimise surface traffic movement with space and time window constraints. Jiang et al. [151] improved the mutation process in the GA and applied a single-point crossover operator for small-scale taxiway optimisation. The algorithm has been tested on less than 20 aircraft. The concern over carbon emissions from idling aircraft has been the research motivation for "green" airports in the future. Ravizza et al. [152] presented a novel model to optimise conflicting objectives: taxiing time and fuel consumption. The proposed environmental taxiway optimisation was structured with an energy-efficient approach for ground controllers to monitor the emission level in an airport. Weiszer et al. [153] proposed a model with environmental and economic analysis to achieve sustainability in taxiway, runway, and airport shuttle bus schedules as a total solution using NSGA-II. Tianci et al. [154] studied a two-stage PSO algorithm for the speed and fuel optimisation in taxiway movement problems.

3.2.4. Integrated model

The integrated model provided a better control on the interrelated airport resources or sequential relationship between airside activities. The related articles were summarised in **Table 9**. Lee et al. [155] presented a multiple objectives flight schedule model by manipulating the departure times of several flights to enhance the insensitivity to operational irregularities and other disruptions in practical terms. In their model, airline schedule and maintenance routing problem was merged to optimise as the available flights affect the number of airline service provided. Another possible integrated model from the literature is runway scheduling and taxiway optimisation. Runway schedule, taxiway optimisation and gate allocation are the sequential operations when flights arrive at the terminal [156, 157]. This model focused on maintaining a smooth operation between air traffic and airport traffic.

Table 5

Research on meta-heuristics for surface traffic operation – gate assignment problem

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
Gate assignment problem	Single solution meta-heuristics	Memory structure	2004	Interval Exchange TS	TS [158]; Burte force	Min. the number of flights assigned to the apron; min. the total walking distance	[159]
			2012	TS	Exact method#	Min. the total conflicting cost under all worst-case scenario	[160]
			2017	EC algorithm	Layered branch-and-bound algorithm [161]	Max. the buffer time of two successive flight activities; max. the total preference value of the assignment; min. the total cost of arrival, parking and departure	[137]
		Neighbourhood structure	2016	VRNS	Exact method#	Min. the distance for transfer passengers; min. the gate conflict cost; min. the towing movement	[162]
			2017	Adaptive LNS	TS [160]	Min. the conflict cost; min. the tow cost; min. the transfer cost	[163]
			2017	BLS	TS; ILS with descent-base local search; ILS with critical element-guided perturbation; greedy constructive procedure; variants of BLS	Max. the airline preferences for a particular gate; max. the idle time between gate activities; max. the usage of gate space; min. the number of passengers arriving or departing from remote gates; min. the number of tows to terminal gates	[164]
	Biological evolution	Gene	2001	GA	Exact method^	Min. the squared deviation of the idle times of the two successive flight activities	[136]
			2005	MA with local search	TS; variants of Mas; variants of GAs	Min. the total walking distance	[165]
			2016	GA	N/A	Min. the gate idle time	[166]
		Species	2017	BBO	N/A	Min. the expected flight conflict with probabilistic distribution; min. the number of flights assigned to aprons	[167]
	Physics-based algorithm	Energy	2008	Pareto SA	N/A	Max. the airline preferences to particular gates; min. the number of ungated flights; min. the total passenger walking distance	[168]
			2012	Single-leap BB-BC algorithm	Manual method; ground time duration maximisation algorithm (GTMA); BB-BC algorithm	Max. the total time of the gate allocated for all flights	[169]
	Swarm intelligence	Ant	2014	ACO	Exact method#; greedy algorithm	Min. the weighted sum of departure delays, buffer time and matching degree to aircraft with gate	[139]
		Bee	2017	Fuzzy Bee Colony Optimisation (FBCO)	Manual method	Min. the number of flights assigned to remote gates; min. the total walking	[170]

						distance for connecting flights	
		Particle	2017	Improved adaptive PSO algorithm	GA [166]; SA [46]; TS [46]; MA [165]; hybrid SA + TS [46]; Hill-climbing GA [171]; BB-BC algorithm [169]; improved ACO	Min. the idle time variance of each gate; min. the number of flights at parking apron; min. the walking distance of passengers	[172]
	Hybrid meta-heuristics	Integrated	2005	Integrated SA and TS	Brute force method; interval exchange TS [173]; SA [173]	Min. the number of flights assigned to the apron	[47]
			2012	Integrated SA and TS	GA; SA; TS	Min. the walking distance of arrival, departure and transfer passengers	[46]
Gate re-assignment problem	Single solution meta-heuristics	Memory structure	2017	Stochastic EC algorithm	Layered Branch-and-Bound algorithm without robustness [161]; Layered Branch-and-Bound algorithm with robustness [161]; EC algorithm without robustness [137]; Hybrid meta-heuristic [174]; Two-stage heuristic [175]	Min. the expected number of violations against the tow time restrictions	[176]
	Biological evolution	Gene	1999	GA	N/A	Min. the extra delay time by revising the disrupted gate assignment	[138]
	Physics-based algorithm	Energy	2010	Pareto SA	N/A	Max. the total preferences score of the gate assignment; min. the deviation from a planned gate assignment; min. the number of towing operations	[177]
	Swarm intelligence	Ant	2013	ACO	Manual method	Min. the deviation from a planned gate assignment	[178]
Stand allocation problem	Single solution meta-heuristics	Memory structure	2015	EC algorithm	Exact method#; stand decomposition heuristic; time decomposition heuristic; greedy algorithm	Max. the number of aircraft at terminal gates; min. the towing movement	[140]

#: solved by *IBM ILOG CPLEX* Optimisation Studio; ^:solved by Lindo optimisation tool

Table 6

Research on meta-heuristics for surface traffic operation – aircraft maintenance routing problem

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
Aircraft maintenance routing problem	Single solution meta-heuristics	Memory structure	2017	TS	Exact method#	Min. cost for technicians to complete all tasks; min. the variance of the technicians' workload	[179]
		Neighbourhood structure	2016	Very LNS	Exact method#	Min. the total remaining flying time of all flights	[180]
	Biological evolution	Gene	2005	GA	N/A	Min. the total flow time of all maintenance activities	[142]
			2007	Dominance-based GA	Variant of searching scheme of the proposed algorithm	Min. number of workers (electrician and mechanic workers); min. the completion time of the preventive maintenance task	[143]
	Physics-based algorithms	Energy	2014	CA	Exact method#	Min. the total unused legal flying time of the critical aircrafts	[144]

#: solved by *IBM ILOG CPLEX* Optimisation Studio

Table 7

Research on meta-heuristics for surface traffic operation – aircraft ground service scheduling

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
Ground service handling recovery	Biological evolution	Gene	2009	GA	N/A	Min. the deviation of the updated schedule from the original under disruption	[148]
Ground service handling schedule	Single solution meta-heuristics	Neighbourhood structure	2016	VND with LNS	SA [181]; improved SA [182]; GA [183]; LNS [184]	Min. the deviation between the assigned time of operation and the earliest possible time; min. the total completion time of the turn-a-round processes	[44]
	Biological evolution	Gene	2013	GA with hybrid encoding scheme	HA with greedy heuristic	Min. the total tardiness of all flights	[149]
	Physics-based algorithms	Energy	2010	Variant D using SA	Variants of TS; variants of SA	Max. the number of catering activities	[185]

Table 8

Research on meta-heuristics for surface traffic operation – taxiway optimisation

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
Taxiway optimisation	Single solution meta-heuristics	Neighbourhood structure	2016	ILS with receding horizon	FCFS [90]; BRGA [90]; RHC-ACO [95]	Min. the total delay of all flights	[186]
	Biological evolution	Gene	2005	Improved GA	GA; GA with different types of heuristic	Min. the average delay	[150]
			2013	GA	N/A	Min. the total time cost of all aircrafts	[187]
			2015	GA	Comparison between different weighted of the objective function	Min. the weighted cost of single-depot-vehicle scheduling problem; min. the weighted runway delay; min. the weighted taxi time	[153]
			2015	Improved GA	ACO	Min. the total taxiing time of all flights	[151]

Table 9

Research on meta-heuristics for integrated airside operations research model

Model config.	Algorithm classification	Search method/agents	Year	Proposed solution(s)	Benchmarking algorithm(s)	Objective function(s)	Ref.
Integrated airline schedule and maintenance routing problem	Biological evolution	Gene	2007	MOGA	N/A	Min. the delays over 15 minutes; min. the number of cancellation flights	[155]
Integrated runway scheduling and taxiway optimisation	Single solution meta-heuristics	Memory structure	2008	TS	FCFS; manual method	Min. the weighted delay cost in take-off	[156]
	Biological evolution	Gene	2016	GA with local search	N/A	Min. the taxiing time on the airport surface; min. the transport time	[157]

4. Statistical analysis of the latest studies

This section presents the statistical analysis of the delimited articles in accordance with the proposed taxonomy framework and algorithm classification. The selection of the meta-heuristics is usually justified by the required accuracy of the solution, problem complexity and computation time. Indeed, several meta-heuristics has not been studies in airside operations. Although we see meta-heuristics remain a high research potential in various operations research domain, the particular types of meta-heuristics may perform vary in different nature of the problem or modelling methods. Therefore, the summary of this review benefits readers in defining the possible future direction and the trends of the research. The following statistical analysis summarised the 103 articles in the airside operations research using meta-heuristics from Jan 1996 to Sep 2017.

4.1. Distribution of articles by airside activities

After reviewing the relevant journals from the above electronic library, 103 journal articles were successfully extracted and aligned with our selection criteria. Approximate 25% and 24% of the selected articles are grouped in AO in TMA, including FSP and ASSP. It concludes that fleet resources constraints planning and runway scheduling stated important positions of the airside activities. The rank number three of the distribution of airside activities using meta-heuristics is GAP, which is about 21% of the selected articles. Except for the integrated model, the remaining research domain occupied approximate 4-7% distribution. Given the complexity of the formulation in an integrated model, we found that integrated model is the potential research in the field.

Fig. 9. Approximate distribution meta-heuristics application by airside activities

4.2. Distribution of articles by airside activities and publication year

The distribution of publications across years (from Jan 1996 to Sep 2017) is shown in **Fig. 10**. The first journal article related to airside activities using meta-heuristics was published in 1996. There was only sporadic publication of scientific papers in this area between 1997 and 2003. Meta-heuristics research gained popularity after 2004. Large numbers of publications in this research field were found for the period between 2012 and 2017. The timeline of the publication exhibits an increasing trend. We observed that most of the articles in this review fell into the categories of STO and AO in TMA after 2012. The trend also aligned with the **Fig. 9**.

Fig. 10. Publication distribution timeline

4.3. Distribution of articles by meta-heuristics and publication year

The research methodology by year was presented in **Fig. 11**. Single solution meta-heuristics and biological evolution algorithms have been the most popular algorithms throughout the years as most of the algorithms were well developed. Most of the physics-based algorithms and swarm intelligence were developed after 2000 (See **Table 16** and **Table 17** in **Appendix B**). Regarding the development of the meta-heuristics. There has been an increasing trend of using physics-based algorithms and swarm intelligence in airside activities.

Fig. 11. Algorithm distribution timeline

4.4. Distribution of articles by journal

The first four rank journals from the delimited publications includes *Computers & Operations Research*, *European Journal of Operational Research*, *Expert Systems with Applications* and *Mathematical Problems in Engineering*, contribute to 30% of the whole of the selected journals. **Table 10** shows the list of articles regarding the academic journals from 1997 to 2017. The latest literature access was in Sep 2017. There has been an increasing trend in the number of articles issued in the research area of airside activities using meta-heuristics.

Table 10

Distribution of articles by journal

Journal title	Count	Percentage	Ref.
Elsevier - Computers & Operations Research	9	8.7%	[44, 45, 47, 88, 89, 104, 112, 120, 164]
Elsevier - European Journal of Operational Research	8	7.8%	[71, 84, 134, 140, 143, 144, 155, 185]
Elsevier - Expert Systems with Applications	7	6.8%	[46, 82, 110, 111, 128, 163, 169]
Hindawi - Mathematical Problems in Engineering	7	6.8%	[103, 105, 116, 139, 178, 187]
Elsevier - Transportation Research Part C: Emerging Technologies	6	5.8%	[54, 106, 107, 170, 180, 186]
Springer - Journal of the Operational Research Society	5	4.9%	[69, 118, 119, 136, 159]
Elsevier - Applied Soft Computing	4	3.9%	[67, 101, 129, 172]
Elsevier - Computers & Industrial Engineering	4	3.9%	[115, 124, 157, 162]
Elsevier - Journal of Air Transport Management	4	3.9%	[59, 85, 87, 102]
Elsevier - Transportation Research Part E: Logistics and Transportation Review	3	2.9%	[78, 133, 160]
IEEE Transactions on Intelligence Transportation Systems	3	2.9%	[68, 90, 95]
Elsevier - Chinese Journal of Aeronautics	2	1.9%	[53, 62]
Elsevier - Engineering Applications of Artificial Intelligence	2	1.9%	[61, 75]
IEEE Transactions on Systems, Man, and Cybernetics: Systems	2	1.9%	[125, 131]
Informs - Transportation Science	2	1.9%	[93, 137]
Springer - Journal of Global Optimization	2	1.9%	[55, 56]
Springer - Journal of Heuristics	2	1.9%	[80, 126]
Others	31	30.1%	
Total	103		

4.5. Distribution of articles by algorithm contribution and year

The motivation of this section is to describe the trends of the contribution regarding the novel algorithmic components. **Table 11** summarises the distribution of the selected journal articles by the research methods. We defined the research methods into three major categories. Original meta-heuristics is defined as the research methodology of the articles is direct adoption or adopted without revising the algorithmic components, while improved meta-heuristics denoted that the articles contribute either the convergence rate or computational load of the meta-heuristic algorithm by modifying the algorithmic components. Given a similar nature under the same sub-categories of the meta-heuristics, we interpreted that hybrid meta-heuristics only includes the combination of different categories of metaheuristics. The scholar focused on the evaluation of the use of meta-heuristics throughout the year. Importantly, the recent publication also concentrated on the improvement of the algorithm performance and solution quality.

Table 11

Distribution of the number of journal articles by the research methods

Years	Number of articles Original meta-heuristics	Improved meta-heuristics	Hybrid meta-heuristics	Total
1996	-	1	-	1
1997	1	-	-	1
1999	1	2	-	3
2001	1	2	-	3
2004	2	2	-	4
2005	1	4	1	6
2006	1	1	-	2
2007	3	3	-	6
2008	3	1	-	4
2009	2	1	-	3
2010	2	3	-	5
2011	2	2	-	4
2012	1	3	1	5
2013	6	5	1	12
2014	5	4	-	9
2015	5	4	-	9
2016	3	7	1	11
2017	7	8	-	15
Total	46	53	4	103

4.6. Distribution of articles by airside activities and meta-heuristics

In order to provide an in-depth synopsis of the research field, **Table 12** presents a matrix with the row of airside activities in operations research and the column of meta-heuristics classification. The number in **Table 12** indicates the number of publication in each category.

Table 12

Distribution of articles by airside activities and meta-heuristics

Airside activities	Search method/agents	Single solution meta-heuristics		Population meta-heuristics										Integrated meta-heuristics		Total
				Biological evolution		Physics-based algorithms			Swarm intelligence							
		Neighbourhood structure	Memory structure	Gene	Species	Electromagnetic radiation	Energy	Mass	Ant	Bee	Particles	Bat	Cat	SA+TS	SA+VNS	
ATFM	ACA	1		3		1	1									6
	FPO			6							1					7
AO in TMA	ASSP	4	2	10			1	1	3	1	1	1			1	25
	FSP	7	2	11			2		1		2		1			26
STO	AMRP	1	1	2			1									5
	AGSS	1		2			1									4
	TO	1		4												5
	AGAP	3	5	4	1		3		2	1	1			2		22
Integrated			1	2												3
Total		18	11	44	1	1	9	1	6	2	5	1	1	2	1	103

5. Discussion

This unifying review synthesises the abundant publications related to the field of airside activities and meta-heuristics. Practical implications and potential research can be derived from the statistical results. After the analysis of the taxonomy framework of airside operations and the denotation of important literature publications using the meta-heuristics approach from 1997 to 2017, the subsection of airside operations shares similar features in mathematical modelling. The majority of the meta-heuristics can be executed in a wide range of airside operations. ASSP and GAP can be formulated as JSSP modelling, while AGSS is expressed as a constraint-specified VRP model. Although there is no universal rule to define the selection criteria for meta-heuristics, the systematic review of this paper provides a summary of the current state of understanding of meta-heuristics in airside research. The analysis presented herein indicates the important research implications, which are shown as follows:

5.1. Trend analysis of the research domain

Research that involves the use of meta-heuristics for airside research has increased significantly after 2011. It is projected to grow in the future, especially in AO in TMA. The journal publication in this area accounted for 49% of the overall publications on airside research. Application in ASSP and FSP using the Biological Evolution algorithm is the dominant approach and keeps increasing from 2001 to 2017.

5.2. Additional research directions in airside operations research

More effort should be spent on the formulation of modelling and design of reasonable assumption. Due to the limited exploitation ability of classical optimisation techniques, model simplification is often considered to obtain solutions smoothly. However, the solution set with certain restrictive assumptions may vary from the actual solution in practice. For example, flight size should be considered to reduce the severity of a collision between nearby gates. A preference-based gate assignment is also a typical approach to the actual operation. Aircraft from the same airline should be assigned to nearby gates for ease of arranging the ground services and staff rostering. Various algorithms are developed to resolve complex models nowadays. Hence, loosening assumption and model adjustment help to identify suitable and realistic sets of solutions for practitioners. In relation to the literature, a static approach is commonly considered. We observed that there is a several publications adopting stochastic and robust treatments in mathematical modelling that may be a potential for further investigation.

One special challenge in airside research is that the global optimum for all entities is too complex to achieve. Despite the fact that the decision-making follows the top-down approach for airports, airlines, ground handling entities and agents, airside operations between entities are interrelated and interdependent, which can be considered a closed-loop service supply chain modelling. Current research focuses on solving each sub-problem individually as a decomposition approach, and yet, an optimal global solution of airside operations is the ideal situation. Optimisation of a sub-problem does not necessarily imply optimal solution of another sub-problem. Wastage of resources will take place in the non-optimal situations. Corporate strategy for multiple vital operations arises from the literature and tends to reduce wastage of the resources. Possible extension of the ASSP can be incorporated with the AGAP to measure the effect of GDP. By the current literature, optimisation seldom includes the consideration of air traffic control and airspace congestion at a strategic level. For the review of the airport congestion problem, integration of the FFO and the ASSP allows sacrificing travel time to sustain free-flow traffic in airports.

5.3. Trend analysis of the meta-heuristics design

Exploitation and exploration are the two principal performance metric in evaluating the convergence of the meta-heuristics [38, 41]. In general, exploitation ability is described as the ability in searching better solution from a known solution, while exploration ability is interpreted as the ability in escaping the local optimal [41]. Single solution meta-heuristics work well for the problem required higher exploitation ability, while biological evolution performs better for the problem required higher exploration ability.

Biological evolution is the most adopted approach, as the information sharing using crossover operators between populations improve the convergence rate in path searching. As for the categories of AO in TMA, Gene agents under biological evolution category and neighbourhood structure under single solution meta-heuristics category are the representatives of the field. One possible reason is that neighbourhood structure algorithm performs better for the FCFS-like schedule or the problem required higher exploitation ability in searching optimal, as it provides extensive local operators. Therefore, we can also observe similar publication patterns in GAP model under STO category. Memory structure algorithms have less exploitation but exploration ability. The algorithm usually restarted from a memorised solution when the current solution fell into a local optimal.

5.4. Research potential of meta-heuristics

We noticed that there is a few of publication using physics-based algorithms and swarm intelligence in airside operations research comparing with the others. However, the potential of the meta-heuristics shall not be underestimated. The algorithmic structure of physics-based algorithms performs both exploitation and exploration ability at a different portion along with the iterative process. If a solution is expected to be trapped in local optima, the algorithm may direct to revise the solution structure to escape from local optima. The mechanism of swarm intelligence concentrates the balance of exploitation and exploration on enhancing the time for convergence [41]. Few studies have employed hybrid meta-heuristics, physics-based algorithms or swarm intelligence in these fields. As a consequence, there are opportunities to obtain a better solution quality by other meta-heuristics.

Algorithm customisation is a problem-specific method to modify the known algorithms to achieve a better solution quality. The modification work can be done based on the nature of the model, such as mono-versus multi-objective, linear versus non-linear constraints, trajectory-based versus population-based favour, and static versus stochastic modelling. These factors may affect the selection of the appropriate algorithm. It is, however, not feasible to test all the meta-heuristics algorithms for evaluation due to comprehensive parameter turning. Researchers may refer to the literature or review articles to identify a proper group of algorithms for future works. This study helps readers to the researchers to identify the potential research area and highlight the research opportunities for this category of problems.

5.5. Limitations in existing airside operations research

This systematic review considers the operations research in airside activities using meta-heuristic approach to evaluate and access the trend and distribution of the publication of the literature. Only 103 journal articles are extracted in this review. Physics-based algorithm and swarm intelligence are the recent meta-heuristics. Therefore, the publication in the field remains potential research but not statistically significant from the literature. Swarm intelligence is still in a development stage, as we discover that new algorithms were developed recently. There still may be a possibility to have some outstanding swarm intelligence algorithms in the future.

6. Concluding remarks

This paper presents a literature survey of the use of meta-heuristics algorithms in airside research. The significance of airside studies not only provides a high-quality solution within a reasonable amount of time, but pursues the requirement of integration between different sub-problems. More realistic constraints and loosening assumptions are essential in future research, which requires a faster convergence to a near or global optimal solution. The research methodology using meta-heuristics is of importance to the development of sophisticated modelling in airside operations. The analysis presented in this paper highlights the important research area, and the selection of meta-heuristics algorithms from the literature to help readers to identify potential research areas. The proposed taxonomy framework has shown the classification of airside studies. The following remarks can be made regarding this review:

1. A taxonomy framework for the airside operations using meta-heuristics approach is lacking. A comprehensive analysis of each category must be investigated.
2. Mathematical modelling in the airside operations remains a static approach. Current publications on the airside operations research are far removed from the actual practice, and dynamic or stochastic approach in airside operations is the newly emerging research direction considering the robustness of the modelling.
3. General deficiencies of the previous research are highlighted in the discussion. The summary of future research direction guides readers to determine the potential research areas.
4. Current research has stated that meta-heuristics is a promising optimisation technique regarding time and solution quality. Due to the demand for complex or integrated modelling, the use of meta-heuristics may not be able to satisfy the computational needs of resource-constrained problems. Efforts should be made to develop new or modified meta-heuristics algorithms to solve complicated real-world models.

In this review, the airside research involved a large number of practitioners and activities with tightening resources. In view of the limited resources for expanding the capacity of coping with future air traffic demand, optimisation using meta-heuristics remains a high research potential. This unifying survey synthesises the current research progress in airside operations and highlights the benefits of sophisticated modelling and an integrated approach. It can be concluded that research on airside operations using meta-heuristics is a promising area. Physics-based and Swarm intelligence algorithms in airside operations are a relatively new research field that can be addressed in the future.

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Appendix A. Abbreviations

Table 13

List of abbreviations

General aviation terms	
AFP	Airspace Flow Program
AO in TMA	Aircraft Operations in Terminal Manoeuvring Area
ARN	Air Route Network
ATC	Air Traffic Control
ATFM	Airspace and Air Traffic Flow Management
ATM	Air Transport Management
CWL	Crossing Waypoints Location
FCFS	First-Come-First-Served
GDP	Ground Delay Program
TMA / TMC	Terminal Manoeuvring Area / Terminal Manoeuvring Centre
Modelling techniques	
AGSS	Airport Ground Service Scheduling
ALP	Aircraft Landing Problem
AMRP	Aircraft Maintenance Routing Problem
ASSP	Aircraft Sequencing and Scheduling Problem
ATP	Aircraft Take-off Problem
CO	Combinatorial Optimisation
FFO	Flight path optimisation
GAP	Gate Assignment Problem
JSSP	Job Shop Scheduling Problem
STO	Surface Traffic Operation
TSP	Travelling Salesman Problem
VRP	Vehicle Routing Problem
Meta-heuristics	
ABC	Artificial Bee Colony
ACO	Ant Colony Optimisation
EA	Evolutionary Algorithm
GA	Genetic Algorithm
MA	Memetic Algorithm
SA	Simulated Annealing
TS	Tabu Search
VND	Variable Neighbourhood Descent
VNS	Variable Neighbourhood Search

Appendix B. Meta-heuristics classification

Table 14

Examples of single-solution meta-heuristics

Search Method	Algorithms
Neighbourhood structure	Greedy Randomised Adaptive Search Procedure (GRASP) [33]; Meta-heuristic for Randomised Priority Search (Meta-RaPS) [188]; Iterated Local Search (ILS) [16]; ;Variable Neighbourhood Search (VNS) [189]; Variable Reduce Neighbourhood Search (VRNS) [190]; Large Neighbourhood Search (LNS) [191]; Guided Local Search (Guided-LS) [192]; Breakout Local Search (Breakout LS) [193]
Memory structure	Tabu Search (TS) [12]; Ejection Chain (EC) method [194]

Table 15

Examples of biological evolution

Agent	Search Method	Algorithms
Gene	Eugenics	Evolutionary Algorithm (EA) [195]; Evolutionary Strategies (ES) [196]; Evolutionary Programming (EP) [197]; Genetic Algorithm (GA) [17]; Memetic Algorithm (MA) [18]; Genetic Programming (GP) [18]; Differential Evolution (DE) [19]; Scatter Search (SS) [198]
Species	Immigration; Suitability	Biogeography-based optimisation (BBO) [199]; Parallel Evolution Algorithm (PEA) [200]

Table 16

Examples of physics-based algorithms

Agent	Search Method	Algorithms
Electromagnetic radiation	Light propagation	Light Propagation Algorithm (LPA) [56]
	Refracted ray	Ray Optimisation (RO) [24]
Electron	Electric charge	Charged System Search (CSS) [201]
Energy	Explosion; Contraction	Big-Bang Big-Crunch (BB-BC) Algorithm [22]
	Temperature change	Simulated Annealing (SA) [202]; Compressed Annealing (CA) [203]
Mass	Gravitational force	Central Force Optimisation (CFO) [204]; Gravitational Search Algorithm (GSA) [23]
	Electromagnetic force	Black Hole (BH) Algorithm [205]
Mechanical wave	Sound	Harmony Search (HS) [206]; Melody search Algorithm (MSA) [207]; Symphony Orchestra Search Algorithm (SOSA) [208]
Molecule	Water drop	Intelligent Water Drops (IWD) Algorithm [209]
	Liquid surfaces	Ripple Spreading Algorithm (RSA) [210]
	Consecutive reaction	Artificial Chemical Reaction Optimisation Algorithm (ACROA) [211]
Space	Theory of space-time curvature	Curved Space Optimisation (CSO) [212]

Table 17

Examples of swarm intelligence algorithms

Agent	Search Method	Algorithms
Ant	Pheromone communication	Ant Colony Optimisation (ACO) [26]; Ant System (AS) [213]; Ant Colony System (ACS) [214]; MAX-MIN Ant System [215]; Termite Algorithm (TA) [2]
Bee	Division of labour	Artificial Bee Colony (ABC) Algorithm [25]; Optimisation with Marriage in Honey-bees (MBO) [216]; Bee System (BS) Algorithm [217]; Bees Algorithm (BA) [218]; Wasp Swarm Optimisation (WSO) [219]; Bee Collecting Pollen Algorithm (BCPA) [220]
Cat	Division of labour; Social leadership	Cat Swarm Optimisation (CSO) [221]
Wolf	Division of labour; Social Leadership	Grey Wolf Optimiser (GWO) [222]
Fish	Position; Velocity	Artificial Fish Schooling (AFS) Algorithm [223]
Particle	Position; Velocity	Particle Swarm Optimisation (PSO) [28]
Bat	Echolocation; Position; Velocity	Bat Algorithm (BA) [27]
Frog	Aggregating; Position; Velocity	Frogs Leaping Optimisation (FLO) [224]
Roach	Aggregating; Position; Velocity	Roach Infestation Optimisation (RIO) [225]
Dolphin	Aggregating; Position; Social Leadership; Velocity	Dolphin Partner Optimisation (DPO) [226]
Krill	Aggregating; Position; Velocity	Krill Herd (KH) Algorithm [227]
Glowworm	Position; Sensing capability; Velocity	Fruit Fly Optimisation Algorithm (FOA) [228]
	Epigamic selection	Glowworm Swarm Optimisation (GSO) [229]; Firefly Algorithm (FA) [230]
Bird	Eugenics	Bird Mating Optimiser (BMO) [231]
Monkey	Communication; Trajectory	Monkey Search (MS) [232]
Flower	Self-pollination; Allogamy	Flower Pollination Algorithm (FPA) [233]

Appendix C. Common and differentiate variables in each framework of the airside operations research

Table 18

Common and differentiate variables from the literature for airspace and air traffic flow management – aircraft collision avoidance

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
2D trajectory plan	Number of flights; set of flight legs; waypoints; length of the en-route segment; 2D flight path model		[53, 55]	Generic model
3D trajectory plan	Number of flights; set of flight legs; waypoints; length of the en-route segment; altitude profile; 3D flight path model		[56]	Generic model
		Allowance of ground delay program	[54]	Reduce the number of missed detects and false alarms for large scale traffic
		Real time GPS coordinates	[65]	Propose a grid-design to reduce the problem complexity
		Speed regulations; allowance of ground delay program	[57]	Consider the continent-scale; yield zero interacting solution by considering ground delay programme

Table 19

Common and differentiate variables from the literature for airspace and air traffic flow management – flight path optimisation

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
Airspace flow program	Number of flights; set of flight legs; waypoints; length of the en-route segment	Safety margin from obstacles	[61, 64]	Evaluate the performance of the algorithm under five different scenarios
Crossing waypoints location problem			[59, 61, 62, 67]	Generic model
Multi-airport capacity management	Set of nearby airport; estimated time of arrivals/departures; maximum number of flights for arrivals and departures		[68]	Generic model

Table 20

Common and differentiate variables from the literature for aircraft operation in terminal manoeuvring area – aircraft sequencing and scheduling problem

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
Aircraft landing problem	Number of flights; Number of runway; Separation time; estimated time of arrival		[8, 45, 69, 71, 85, 86, 89, 92, 94, 100, 101]	Generic model
		Flights size	[87, 88, 90]	Consider receding horizon to reduce the problem complexity
		Time window of each rolling horizon	[95]	
		Density matrix of wake-vortex	[97]	Estimate the wake-vortex effect and determine the runway schedules
Aircraft sequencing and scheduling problem	Number of flights; Number of runway; Separation time; estimated time of arrival and departure		[102, 103, 105]	
		Constrained position shifting; requirement of mixed-mode operation	[104]	Adopt constrained position shifting for mixed-mode runway operation
		Uncertain time of arrival and departure; requirement of mixed-mode operation	[78]	Introduce the min-max regret approach in hedging uncertainties of runway operation
Aircraft take-off problem	Number of flights; Number of runway; Separation time; estimated time of departure	Re-ordering cost	[93]	Predict the take-off time by calculating the possible turn-a-round processes to formulate a take-off schedule
Terminal traffic flow modelling	Number of flights; Number of runway; Separation time; estimated time of departure; TMA resources		[106, 107]	Adopt the alternative graph for ATC-TMA; consider the re-routing strategies in TMA

Table 21

Common and differentiate variables from the literature for aircraft operation in terminal manoeuvring area – fleet schedule planning

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
Airline schedule recovery	Number of flights; set of flight arcs; arrival and departure time; initial schedule; disruption time		[80, 82, 108, 109, 111]	Generic model
		Allowance of long delay time	[110]	
		Stochastic distribution of arrival and departure time	[81]	Focus on short-haul flights disruption planning
		Stochastic distribution of arrival and departure time; robust criteria	[112]	Develop a robust schedule to tackle stochastic event
Airline scheduling	Number of flights; set of flight arcs; arrival and departure time; set of connecting flights pair		[115]	Evaluate the proposed algorithm using a two stage model with the Monte Carlo simulation
Airline scheduling and crew-pairing problem	Number of flight; set of flight arcs; set of legal pairings; arrival and departure time; cost of pairings; number of crews		[116]	Combine airline scheduling and crew-pairing for short-haul flights business
Crew recovery	Set of flight arcs; arrival and departure time; disruption time; number of disrupted crews		[117]	Generic model
Crew-pairing problem	Set of flight arcs; set of legal pairings; arrival and departure time; cost of pairings; number of crews		[118-120, 123, 124, 126-129]	Generic model
		Duty regulation	[125]	Reduce the computation time significantly for practical usage as short-haul flights usually have tight schedules
Fleet schedule recovery (integrated airline and crew-pairing recovery	Set of flight arcs; set of legal pairings; arrival and departure time; cost of pairings; number of crews; disruption time		[84, 131]	Consider disruption for short-haul flights recovery model
Fleet schedule recovery (integrated airline and passenger recovery	Set of flight arcs; set of legal pairings; arrival and departure time; disrupted passengers		[132-134]	Consider disruption on passengers and reallocate the disrupted passengers to airline

Table 22

Common and differentiate variables from the literature for surface traffic operation – gate assignment problem

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
Gate assignment problem	Set of terminal gates; arrival and departure time; walking distance between gates		[136, 139, 165, 169]	Generic model
		airline preferences	[168]	Take airline preferences into account of gate assignment
		Set of aprons	[47, 159, 166, 172]	Consider the parking slot before entering gates
		Set of aprons; airline preferences	[137]	Formulate the robust GAP using Clique Partitioning Problem; evaluate the robustness a schedule by achieving the minimum buffer time
		Set of remote gates	[46, 170]	
		Set of remote gates; airline preferences	[164]	Develop a joint-objectives from the literature; successfully adopt efficient meta-heuristic algorithm in practical usage
		Flight connections for the transfer passengers	[162, 163]	Measure the robustness by considering the expected gate conflicting cost and tow frequency; transform the quadratic formulation which can be solved by exact method
		Set of aprons; probabilistic distribution of arrival and departure flights	[167]	Generic model
		probabilistic distribution of arrival and departure flights; stochastic turn-a-round processing time	[160]	Formulate the stochastic arrival time of flights with a left-skewed triangular distribution in the gate assignment problem
Gate re-assignment problem	Set of terminal gates; arrival and departure time; walking distance between gates; disruption time		[138]	Generic model
		set of tow vehicles; stochastic arrival and departure time	[176]	Reassign the gates and consider the towing cost for surface traffic flow
		Gate sizes	[177, 178]	
Stand allocation problem	Set of terminal gates; arrival and departure time; walking distance between gates; set of apron		[140]	Generic model

Table 23

Common and differentiate variables from the literature for surface traffic operation – aircraft maintenance routing problem

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
Aircraft maintenance routing problem	Set of maintenance checks; number of workforce; remaining legal flying times; maintenance regulation		[142, 143, 180]	Generic model
		Duration of a work shift; skills profile of technicians	[179]	Consider the trade-off between the fairness of the technicians' workload and total labour cost
		Maintenance priority	[144]	

Table 24

Common and differentiate variables from the literature for surface traffic operation – aircraft ground service scheduling

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
Ground service handling recovery	Set of ground service handling activities; disruption time; initial schedule		[148]	Generic model
Ground service handling schedule	Set of ground service handling activities; set of ground service handling vehicles; set of visiting node; vehicle capacity		[44, 149]	Formulate the problem as vehicle routing problem with time window
		Skills profile of technicians; set of catering services	[185]	

Table 25

Common and differentiate variables from the literature for surface traffic operation – taxiway optimisation

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
Taxiway optimisation	Set of taxiway arc; arrival and departure time; maximum taxiing speed of flights		[150, 151, 186, 187]	Proposed a taxiway routing following the predefined runway schedule
		Fuel consumption induced by flight movement on ground	[153]	Propose a model resolving no terminal gates airport; evaluate the algorithm by different weighted objective functions; include fuel saving in taxiing

Table 26

Common and differentiate variables from the literature for integrated airside operations research

Model config.	Variables		Ref.	Remarks
	Common	Differentiate		
Integrated airline schedule and maintenance routing problem	set of maintenance checks; maintenance regulation (last maintenance check); number of work force; initial airline schedule		[155]	Proposed an integrated model to develop an airline schedules and their maintenance routing schedules induced by preventive maintenance
Integrated runway scheduling and taxiway optimisation	Set of taxiway arc; arrival and departure time; maximum taxiing speed of flights; Set of terminal gates		[157]	Focus on the conflict free taxiway routing after landing
	Number of flights; separation time; estimated time of departure; set of taxiway arc		[156]	Integrated the take-off schedule with uncertain taxiing time

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