# Toward a More Realistic, Cost-Effective, and Greener Ground Movement Through Active Routing: A Multiobjective Shortest Path Approach

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***Abstract*—This paper draws upon earlier work, which developed a multiobjective speed profile generation framework for unimpeded taxiing aircraft. Here, we deal with how to seamlessly integrate such efficient speed profiles into a holistic decision-making framework. The availability of a set of nondominated unimpeded speed profiles for each taxiway segment, with respect to conflicting objectives, has the potential to significantly impact upon airport ground movement research. More specifically, the routing and scheduling function that was previously based on distance, emphasizing time efficiency, could now be based on richer information embedded within speed profiles, such as the taxiing times along segments, the corresponding fuel consumption, and the associated economic implications. The economic implications are exploited over a day of operation, to take into account cost differences between busier and quieter times of the airport. Therefore, a more cost-effective and tailored decision can be made, respecting the environmental impact. Preliminary results based on the proposed approach show a 9%–50% reduction in time and fuel respectively for two international airports: Zurich and Manchester. The study also suggests that, if the average power setting during the acceleration phase could be lifted from the level suggested by the International Civil Aviation Organization, ground operations may simultaneously improve both time and fuel efficiency. The work described in this paper aims to open up the possibility to move away from the conventional distance-based routing and scheduling to a more comprehensive framework, capturing the multifaceted needs of all stakeholders involved in airport ground operations.**

***Index Terms*—Active routing, multi-objective shortest path problem, fuel consumption, economics, sustainability, A-SMGCS.**

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## I. Introduction

Energy-efficient air transportation has been identified as one of the Grand Challenges for Control in 2011 [1], with the aim of having efficient, robust, safe, and environmentally aware air traffic management (ATM). As pointed out in [1], the problem is in essence a distributed, large-scale, and multi-objective control problem with potential trade-offs between objectives such as fuel burn, operating costs, delays, and system throughput. Therefore, apart from technological improvements for fuel efficiency, multi-objective control (search) techniques that simultaneously aim to improve these various objectives are prevised as the key to unfold and exploit such a hidden and rather complex relationship. Among these objectives, the ability to quantify fuel burn not only has a direct link to managing the airline's cost, but it also provides a quantitative means by which the environmental impact can be thoroughly examined and weighted in the decision making process. This has the potential to move the air transportation sector towards more cost-effective and greener operations.

Whilst only a fraction of an aircraft's journey consists of taxiing, this makes a significant contribution to the running cost of an aircraft. This is particularly the case at larger airports and especially for short-haul flights, as jet-engines are designed to operate optimally at cruising speed, and are considerably less efficient when taxiing. It is estimated that fuel burnt during taxiing alone represents up to 6% of fuel consumption for short-haul flights, totaling 5 m tons of fuel per year globally [2]. There seems to be a similar lack of multi-objective approaches in airport ground operations planning. In research towards the Next Generations Air Transportation System (NextGen) in the U.S. [3] and Single European Sky ATM Research (SESAR) program [4], the differing objectives such as fuel burn, operating costs and delays for ground operations are often considered capable of being reconciled. Therefore, considerable effort has been put into the capacity and delay aspects of planning, with little quantification of the associated environmental effects [5].

Although taxi operations are often the largest source of emissions in a standard landing take-off (LTO) cycle around airports [6], many studies that focus on fuel consumption on the airport surface assume an average value for fuel flow during taxi without explicitly accounting for the differing fuel consumption during idling, accelerating from a stop, taxi at constant speed, and turning, perhaps due to a lack of a detailed fuel burn estimation for airport ground operations. As a result, fuel burn, associated surface emissions, and airline's cost are usually considered to be reduced on the same path while reducing taxi times.

As pointed out in [7] and [8], the amount of fuel consumed is an important metric for benefit assessment of congestion control methods, and its detailed estimation plays an important role in calculating the environmental impact of air traffic operations. A trend towards employing a data-driven approach for the modeling of fuel consumption [8], [9] can be observed. The aim is to distinguish contributions to the total fuel consumed on the surface from different taxi phases. In [8], assumptions were made for each of the taxi phases: 4% of take-off thrust is used for "ground idle," 5% for "taxi at constant speed or deceleration," 7% for "turning," and 9% for "acceleration." Higher breakaway thrust (up to 20%) and constant speed thrust (7%) were also investigated. Preprocessing the detailed operational aircraft position data for each flight yields information for different taxi phases. Fixed durations are assumed for acceleration after stop and for a perpendicular turn. The authors concluded that the fractional contribution of each phase to the total fuel consumption does not change, and that stop-and-go conditions constitute about 18% of fuel consumption during surface operations, irrespective of assumptions about the thrust level. Therefore, eliminating such stop-and-go situations would reduce the daily and annual fuel consumption as well as emissions. Furthermore, Nikoleris *et al.* [8] identified that idling and taxi at constant speed or braking are the largest fuel consumption contributors, and are sensitive to the thrust level assumptions for these states. In [9], taxi fuel burn is modeled as a linear function of several potential explanatory variables including the taxi time, number of stops, number of turns and number of acceleration events, estimating the coefficients using operational aircraft data and least-squares regression. Their analysis revealed that although the taxi time is the main driver, the number of acceleration events is also a significant factor in determining taxi fuel consumption, and will also need to be considered in ground movement studies. In addition, results revealed that the assumed 7% thrust value by ICAO for all ground operations is overestimated in most cases, but significantly underestimated for some aircraft types.

The conclusions drawn in [8] and [9] call for a more elaborate ground movement decision support system. Such a system should be able to address:

1) The number of acceleration events: apart from reducing such events at the strategic level during optimization, to avoid routes consisting of many turning segments, the increased realism in planning is also a determining factor; more realistic planning means that pilots can execute such decisions more faithfully to reduce the number of additional acceleration events which may be required to make up for differences between the actual and instructed speeds.
2) The acceleration thrust level and its duration: it is worth pointing out that assumptions made in [8] for a fixed acceleration rate and its duration are not realistic and will only lead to a constrained search space for the routing and scheduling problem (as will be seen in the results in this paper), leading to inferior solutions. Choosing appropriate acceleration rates and durations to reduce the amount of time spent on the "acceleration" and "constant speed" phases will reduce overall fuel consumption.

As indicated in [8], there is a lack of consensus regarding thrust settings and time required for each maneuver. Moreover, the increase in acceleration thrust has little effect on total fuel and emission values, which implies that a slightly higher acceleration thrust may be beneficial in both time and fuel efficiency. Having a decision support system, which can take into account different thrust settings and their corresponding durations, will facilitate decision makers to evaluate the best possible practice and regulations for a specific airport under investigation.

The main costs associated with airport ground movement mainly consist of costs for fuel, aircraft operation and the use of the airport. Fuel consumption and its economic cost have been a concern of the aviation industry for decades [10], and currently constitutes one of the largest operating cost for an airline. Aircraft costs [11], such as maintenance, crew and opportunity costs, also contribute to total airline operations expenditure. In [12], airport opportunity cost is defined as every minute during which the airport infrastructure is used in an inefficient way, particularly during the peak traffic period. Congestion is faced by many airports, especially during peak periods, thus many resources are scarce, including runway and taxiways. Congested airports have applied congestion pricing schemes since the 1960s, to mitigate this problem during hours with high traffic demand [13]–[15]. The idea is to charge access fees for aircraft based on daily traffic patterns to reduce delays. Advanced surface decision support systems should take all of these costs into account in a holistic way so that the most cost-effective planning can be achieved. This implies that the preferable planning solution may vary over a day of operation. With the right pricing scheme, taking into account the multi-faceted needs of all stakeholders involved in airport ground movement, planning solutions will be more acceptable. The overall economic impact on the airlines and airports will be reduced, while time efficiency improved. This will also lead to an overall reduction in greenhouse gas emissions associated with fuel consumption, and a reduction in engine exhaust pollutants that can cause illness and premature mortality [10].

In the light of the above discussion, the overriding objective of this paper is to introduce a holistic decision making framework, named the Active Routing (AR) framework. At the heart of this concept are multi-objective search techniques applied to multiple interconnected components (from multi-objective speed profile generation to route planning). The integration of unimpeded efficient speed profiles, generated in [16], into a routing and scheduling framework enables the investigation of the potentially better power settings and their durations for each individual aircraft in a collaborative, complex and dynamic network environment. Due to the multi-objective nature of the proposed approach, the inclusion of the proposed economic search will assist the decision maker to choose the most appropriate planning solution from a Pareto set according to the current airport operational mode.

This paper is organized as follows: Section II introduces the proposed AR framework; the relation of the proposed framework to multi-objective shortest path problems (MSPP) is also highlighted; Section III introduces a particular implementation of the MSPP, which is based on our previous work [17]; the proposed economic search and decision making framework is discussed in Section IV; Section V presents comparisons of the proposed AR approach with different existing routing approaches, in terms of both their realism and efficiency, evaluated using a heuristic airport ground simulator; sensitivity analysis is also carried out in this section; finally, conclusions are drawn in Section VI, highlighting the important contributions of the work and potential future directions.

## II. The Active Routing (AR) Framework

Conventional routing and scheduling approaches, such as [18]–[22], are formulated as a single-objective shortest path problem (SSPP), where the main concern is to minimize either the total taxi time or a weighted sum of different objectives, such as the time, the delays of the route and the target time for departure. The airport ground movement problem presented in this paper represents a real-world instance of a multi-objective shortest path problem (MSPP), where the aim is to find a set of approximate Pareto optimal (efficient) routes between the parking position on the apron and the runway.

### A. Shortest Path Problems for Airport Ground Movement

The existing research into the SSPP formulation of the airport ground movement problem, can be classified into two categories: a) *sequential approach*, where routing is carried out in a pre-determined sequence; b) *integrated approach*, where routing and scheduling are considered in a combined model. In the sequential approach, the outputs of a separate scheduling stage are utilized by shortest path search algorithms such as Dijkstra's [17] and A* [21] algorithms, which route aircraft one at a time. These algorithms are adapted to take previously routed aircraft into account, with time constraints ensuring safe separations between aircraft. In the integrated approach, the problem is formulated either as a mixed-integer linear programming problem [19], [20] or in the framework of heuristic search methods [23], [24]. The $k$-shortest path [25] algorithm is a derivant of SSPP.

The multi-objective shortest path problem (MSPP) is a direct extension of the SSPP, where each edge has a vector of multiple costs. Modification of the Dijkstra's algorithm [26] for the bi-objective case dates back to Hansen [27] and its multi-objective version was presented in [25]. There are three main approaches to solve a MSPP: a) enumerative approaches such as label correcting [28] and label setting [25], b) ranking methods [29]; and c) heuristic search based approaches [30], [31]. Enumerative approaches work similarly to Dijkstra's algorithm apart from that the objectives at the investigated node are now evaluated using the non-dominance concept. During the last few decades, other variants within this category have been proposed with the aim of speeding up the search if certain heuristics are also available [32]–[34]. However, in the worst case, the number of Pareto optimal paths can grow exponentially with the number of nodes. Therefore, the problem may become computationally intractable with even a small number of considered objectives. In light of the mentioned drawbacks, ranking methods have been developed to approximate Pareto optimal solutions or a subset of the true Pareto front. A ranking procedure proposed by Climaco and Martins [29] for the bi-objective case generates a sequence of $k$-shortest paths with respect to the first objective function, until the path with the minimal value with respect to the second objective function is obtained, leading to a Pareto front of all optimal paths. However, if the value of $k$ is bounded, only not optimal solutions are found. Metaheuristic search based approaches [30], [31] also do not guarantee optimality, but are showing promising features for dealing with non-additive weights, and reducing computational time, especially when the scale of the network is fairly large.

For the problem in this paper, due to the existence of multiple efficient speed profiles for each segment, the weights for each segment, i.e. the fuel consumption and taxi time, are no longer a vector, but a matrix. Vectors within the matrix provide trade-offs among conflicting objectives. The introduction of this matrix for each segment is equivalent to having parallel segments for any two connected nodes, leading to a very complex directed multigraph. For clarity, the term "segment" in this paper has an identical meaning to the term "edge" in multigraph theory, but "segment" is used here since the term "edge" in the context of airport ground movement, as defined in [16], already represents the smallest constituent within a segment. The airport ground movement problem has been formulated here as an MSPP. To the best of our knowledge, apart from [17], which is based on ranking methods, we are not aware of any MSPP algorithms being applied to airport taxiing planning. The proposed AR framework is based on [17], with an additional decision making module to consider the different interests of the stakeholders.

It is worth pointing out that the presented AR framework is fairly general. Therefore, any solution approaches for the MSPP are potentially feasible for the AR framework and worth further investigation.

### B. Description of the AR Framework

The proposed AR concept is a general (i.e. can be extended to $n$ objectives) and complete framework combining both search strategy and decision making. The active routing name acknowledges: 1) the seamless integration of the generated multi-objective speed profiles in the search for the better routes and schedules, and 2) the proactive consideration of the multifaceted needs of all stakeholders and different operational scenarios. The AR framework is illustrated in Fig. 1. Based on the potential routes, multi-objective speed profiles are generated. Then, the selected speed profile determines the route and schedule of the aircraft, imposing time constraints for the subsequent aircraft. The key component that links $n$ objective functions is the generated multi-objective speed profiles.

Without loss of generality, in this paper, two objectives are considered. The objectives, namely the total taxi time $TT$ and the fuel consumption $TF$, are defined in (1):

$$\begin{aligned} TT &= \sum_{i\in A} g_1 = \sum_{i\in A} T\left(q_l, y_i^j\right) \\ TF &= \sum_{i\in A} g_2 = \sum_{i\in A} F\left(q_l, y_i^j, w_i\right) \end{aligned} \tag{1}$$

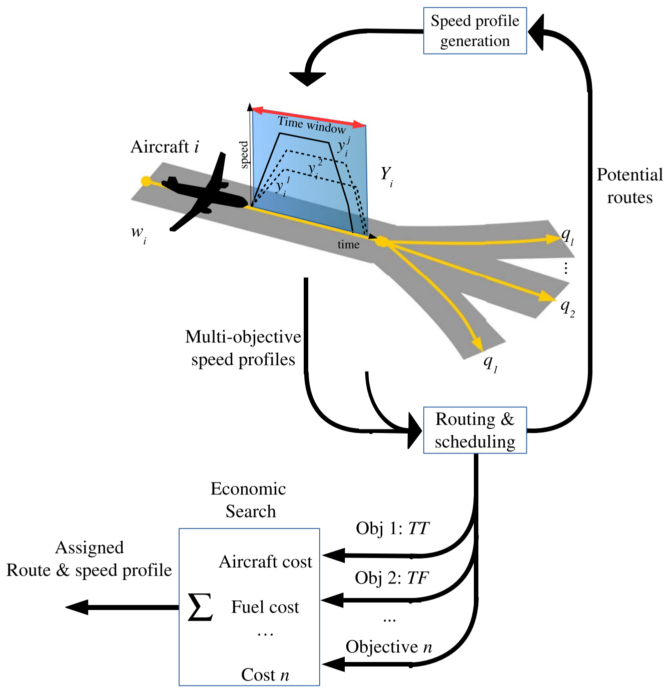



Fig. 1. Active routing framework.

where, $T(q_l, y_i^j)$ is a function which returns the travel time of a single aircraft $i$ on an allocated route $q_l$ following the $j$-th speed profile $y_i^j$ belonging to a set of efficient speed profiles $Y_i$ from the source to the destination, as generated in [16]; $F(q_l, y_i^j, w_i)$ is a function which returns the amount of fuel burn during taxiing for each aircraft $i \in A$ of weight category $w_i$. Interested readers are referred to [16] for the detailed definitions of these two functions and the speed profile generation block.

It is worth noting that neither the definitions of the objective functions described therein nor the MSPP method which are explained in the next section are mandatory in the AR Framework. Other objectives which are derivable from the speed, such as emissions and noise, can also be incorporated into the framework. Irrespective of the actual implementation of each function block shown in Fig. 1, the aim of the AR framework remains the same, which is to route each aircraft $i$ following the speed profile $y_i^j$ on the route $q_l$ in an efficient manner, respecting time constraints imposed by other aircraft while preventing conflicts between them. Time constraints will be discussed in detail in Section III-B.

The decision making block (economic search) takes into account conflicting interests among all stakeholders. The most cost-effective decision will be made with respect to the current airport operational situation, therefore being able to address the dynamic airport environment.

In the next section, an implementation of this framework is introduced.

## III. A Multi-Component and Multi-Objective Approach

The AR framework combines two multi-objective components into a global search problem:

1) The multi-objective speed profile generation problem.
2) The MSPP for routing and scheduling.

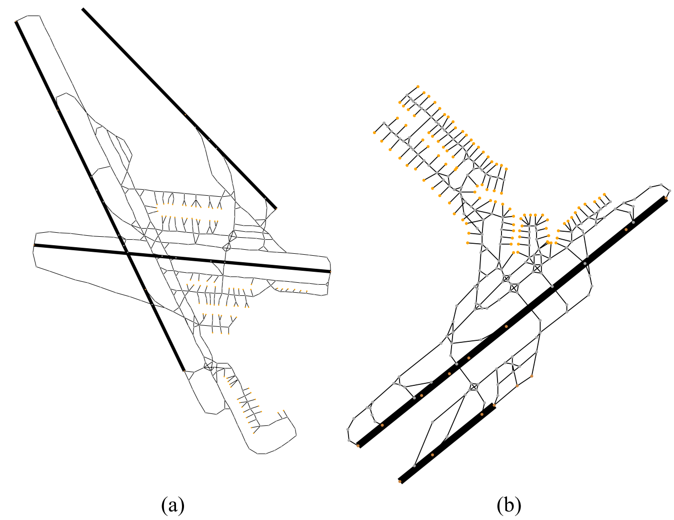



Fig. 2. Directed graph representation of the airport surface for (a) Zurich Airport and (b) Manchester Airport.

The solution of the ground movement problem requires the solution of each of the subproblems. Furthermore, although the speed profile generation problem is independent of the MSPP, it will affect its solution, and the generated speed profile will be affected by constraints given by the routing and scheduling. This type of optimization problem is also known as *multi-component optimization* [35], examples of which include the traveling thief problem [35], the vehicle routing problem under loading constraints [36] and the combined runway sequencing and routing problem [37]. In order to address this combined optimization problem, a sophisticated integrated procedure based on [17] is employed in Section III-A.

### A. An Implementation Instance of the MSPP and the AR

As discussed in [16] and [17], the airport surface is represented as a directed graph, with edges and vertices corresponding to taxiways and crossings, intermediate points or sources/destinations such as gates, stands and runway exit points, respectively, as can be seen in Fig. 2. Intermediate points are placed to ensure a safe separation between two adjacent aircraft. Aircraft are considered to occupy edges and only one aircraft can travel along an edge at a time, enforcing minimum safety distances between aircraft.

Ravizza *et al.* [22] presented a single-objective routing and scheduling algorithm, named the Quickest Path Problem with Time Windows (QPPTW), to find routes and schedules with the minimum total taxi time. The QPPTW algorithm routes aircraft sequentially according to their pushback/landing time taking into account taxiways reserved by previously routed aircraft. Once the route is assigned to an aircraft, it does not change whenever the next aircraft is processed. In order to address the MSPP, the $k$-QPPTW algorithm, which was first presented in [17] and [38], is employed in this work and reproduced here for completeness. The speed of aircraft is crucial for the routing and scheduling algorithm to establish the time interval for which aircraft will occupy individual edges. Therefore, these two subproblems are interconnected, where the route and schedule for a new aircraft can be derived only after searching for the speed profile of the preceding aircraft. This integrated procedure is described in Algorithm 1, which approximates the Pareto front by only generating $p$ points on it.

**Algorithm 1:** Integrated procedure for trade-off analysis.

```
1  Sort aircraft by their pushback/landing time;
2  for a = 1 to p do
3      for each aircraft i do
4          Generate the shortest k routes using the
             k-QPPTW algorithm w.r.t. to time windows;
5          for each route k for aircraft i do
6              Approximate the Pareto front of both
                 objectives using PAIA or the heuristic;
7          end
8          Generate the combined Pareto front for the
             source-destination pair for aircraft i;
9          Discretize this Pareto front into p roughly equally
           spaced solutions;
10         Select the a-th solution and reserve the relevant
             route for aircraft i;
11     end
12     Save the accumulated values for all aircraft for both
         objective functions for the global Pareto front;
13 end
   Result: Approximation of the global Pareto front
```

The $k$-QPPTW algorithm schedules the whole set of aircraft in each iteration (lines 3–11) and a single point on the Pareto front is obtained. As $a$ is incrementally increased (line 2), alternative points on the Pareto front, gradually moving from the most time-efficient to the most fuel-efficient solutions, are found by the $k$-QPPTW algorithm. Pushback/landing times determine the sequence (line 1) in which the algorithm considers the aircraft. The $k$ shortest routes in terms of taxi time for each aircraft $i$ are obtained by assuming constant speed $v_{\text{straight}}$ and $v_{\text{turn}}$ for straight and turning edges, respectively (line 4). The generated routes are subject to constraints imposed by other taxiing aircraft, as described in Section III-B. For each route, two speed profile generation approaches based on a Population Adaptive Immune Algorithm (PAIA) and heuristics [16] are adopted to approximate the Pareto front of speed profiles subject to constraints imposed by previously scheduled aircraft and their reservations (lines 5–7). For the given source destination pair of aircraft $i$, line 8 combines the different Pareto fronts for $k$ routes by removing all dominated solutions in order to obtain the global Pareto front. The resulting Pareto front is discretized into $p$ solutions with approximately equal space between them (line 9). The combination of non-dominated solutions and discretization of the resulting Pareto front is illustrated in Fig. 3.

In line 10, the algorithm selects the $a$-th discretized solution on the Pareto front to schedule aircraft $i$ using the route and speed profile of that solution. The lines 3–11 are iteratively executed to route all aircraft from the dataset and accumulate the total taxi time and fuel consumption in order to generate a single solution on the global Pareto front (line 12).

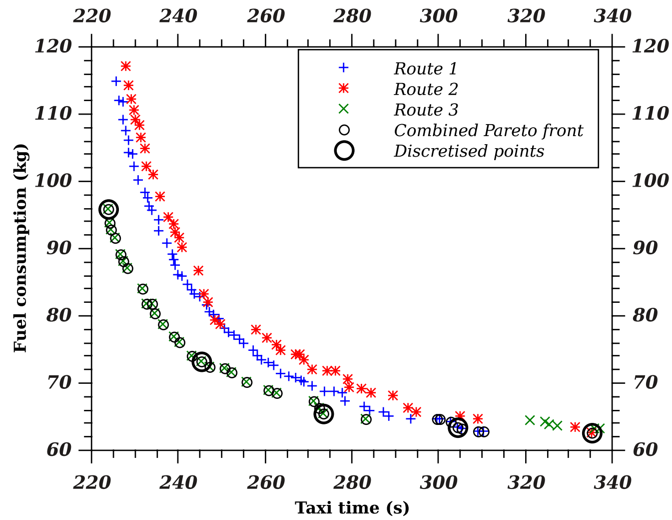



Fig. 3. Combined approximation of the Pareto front from three different routes and $p = 5$ discretized points.

*B. Constraint Handling*

During routing, scheduling and speed profile improvement, the generated routes and speed profiles must conform to: a) physical constraints related to taxiing of a single aircraft such as maximum speed and maximum acceleration; b) constraints related to interactions of multiple aircraft taxiing on the airport surface. The physical constraints are handled by the speed profile generation algorithm [16]. The constraints related to interactions of multiple aircraft ensure that a safe distance between aircraft is maintained during taxiing. For this purpose, each edge $e$ of the graph representing the airport surface has a set of time windows $TW_e$ assigned, which correspond to the time intervals when the edge is not used by any other aircraft. For each aircraft $i$, the time interval $(t_{i,e}^{\text{start}}, t_{i,e}^{\text{end}})$ corresponding to its traversal over the edge $e$ must conform to $TW_e$ so that $(t_{i,e}^{\text{start}}, t_{i,e}^{\text{end}}) \subseteq TW_e$. Algorithm 1 takes time windows into account on two occasions:

1) The $k$-QPPTW algorithm in line 4 generates the shortest $k$ routes using constant speeds, as described in Section III-A. The shortest $k$ routes consist only of edges for which time windows are available;
2) The generated efficient speed profiles (line 6) for the above routes must respect $TW_e$.

As speed profiles are constructed over segments, they span multiple edges. Furthermore, as speed profiles are constructed beforehand, without knowing the available time windows, for each edge $e$, the algorithm has to check conformance of $(t_{i,e}^{\text{start}}, t_{i,e}^{\text{end}})$ with $TW_e$ as illustrated in Fig. 4.

As mentioned above, $TW_e$ for edge $e$ corresponds to a time when $e$ is not used. Therefore, $TW_e$ will be constantly adjusted by excluding the time used by any already routed aircraft as shown in Fig. 5(a). When the next routed aircraft $i$ enters the system, its time interval $(t_{i,e}^{\text{start}}, t_{i,e}^{\text{end}})$ will be calculated, as illustrated in Fig. 4. When there are no conflicts, $i$ will be routed using the calculated $(t_{i,e}^{\text{start}}, t_{i,e}^{\text{end}})$, as shown in Fig. 5(b).

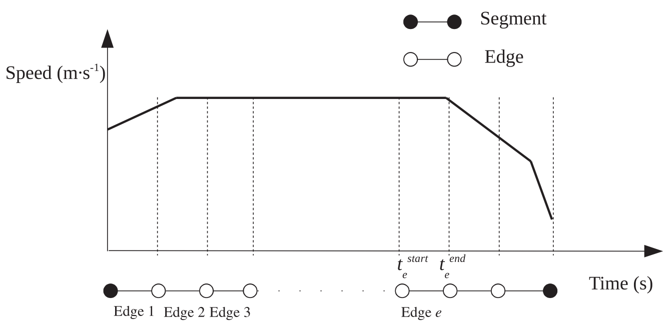



Fig. 4. Speed profiles have to comply with time windows imposed on edges.

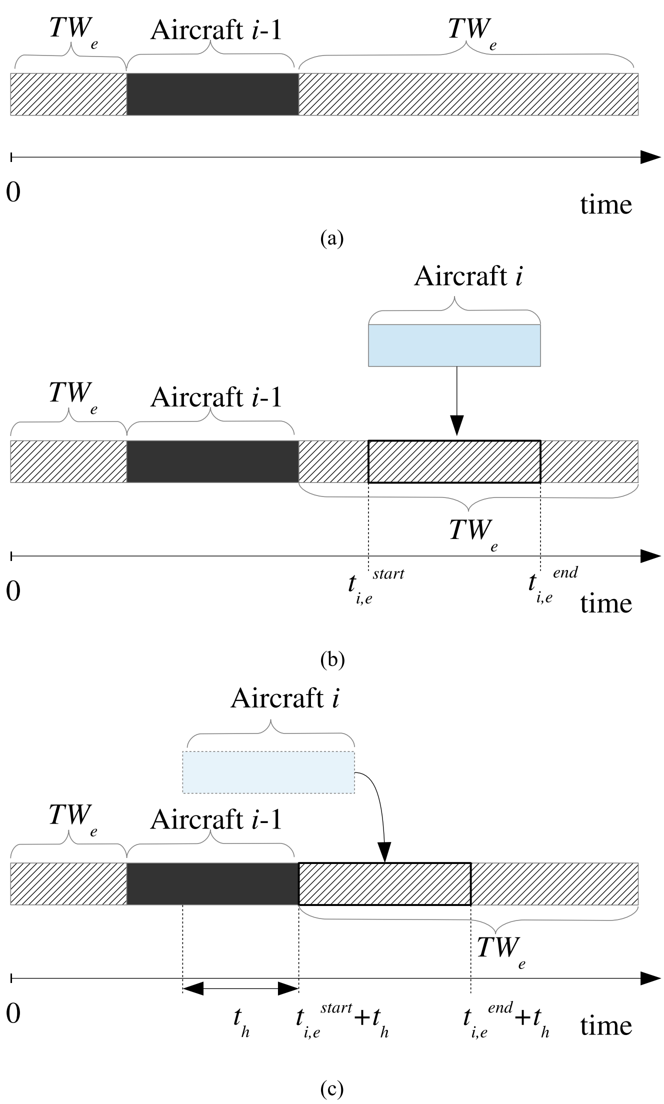



Fig. 5. (a) Time window for edge $e$ corresponds to a time when the edge is not used. (b) If aircraft $i$ is routed, the time window is readjusted. (c) In the case of a violation, holding is applied until aircraft $i$ can be accommodated.

In case of a conflict when no feasible speed profiles exist, holding for the time $t_h$ is applied to all generated speed profiles for the route containing the particular edge in conflict, so that $(t_{i,e}^{\mathrm{start}} + t_h, t_{i,e}^{\mathrm{end}} + t_h) \subseteq TW_e$ as shown in Fig. 5(c). In this case, $TW_e$ will be adjusted accordingly. Otherwise, speed profiles violating $TW_e$ will be discarded during the search, the remaining feasible speed profiles will be used for routing, and $TW_e$ adjusted. It is worth noting that $TW_e$ is not only adjusted when edge $e$ is in use as mentioned above. Other edges, while they are in conflict with edge $e$, will also induce adjustment of $TW_e$. Two edges are considered in conflict if the distance between them is less than the safe distance. A set of efficient speed profiles will ensure that the best possible speed profile is chosen with respect to $TW_e$.

## IV. Economic Search and Decision Making

For a decision support system, the decision maker is responsible for choosing just one of the solutions found by the algorithm, which will then be implemented. The solutions on the obtained Pareto front are only local optima, and additional cost information is required for the decision making. This fact, which is often omitted in multi-objective search studies, is tackled in this section. The conceptual framework presented in this section paves the way to technical/environmental/economic improvement of the airport operations performance by managing the planned taxiing in a better way. A holistic simplified model can consider three cost categories related to the taxiing:

1) Fuel cost is one of the key aspects for the sustainability of the aviation industry, particularly considering renewable fuel [39].
2) Non-fuel aircraft cost. Every minute of aircraft time represents a cost, which is mainly (in terms of [40]):
   a) usage/wear: maintenance to perform at a fix interval,
   b) opportunity cost: revenues missed because the aircraft is not used for profitable business i.e., flying passengers,
   c) various variable operation costs, such as crew cost.
3) Airport opportunity cost, as defined in [12]: every minute for which the airport infrastructure is used in an inefficient way. A longer than expected taxiing time for an aircraft not only means that it can miss its designated slot in the take-off queue, but can also have a network wide effect on other aircraft. The faster the taxiing, the more aircraft can pass in the same time frame, thus reducing the chance that the runway is unused due to missed slots. Consequently, the faster the taxiing, the cheaper the unitary airport opportunity cost for each aircraft.

Since different periods during the day have different demands (peak vs. off-peak), the costs for 2) and 3) change over the day. Moreover, the cost for 3) will vary greatly between airports: some airports are very busy while others are underused. Airport opportunity cost includes a number of items, mainly related to infrastructure construction, maintenance and management [41]. The estimation of the airport opportunity costs needs to include a number of drivers: size (i.e., economies of scale), public vs private ownerships, locations, type of airlines (low cost vs. traditional), etc. The most common way to estimate these relies on marginal cost (since the early work [42], [43]). Bottaso and Conti [44] investigate the cost function focusing on ownership forms and economies of scale, showing that economies of scale exist, but tend to gradually decrease with the scale of operations. They also show that private airports have been more efficient than public-mixed ones (even if the gap is reducing). Martín *et al.* [45] identifies the drivers of airport opportunity cost flexibility by estimating a short-run stochastic cost frontier over a database of 194 airports worldwide between 2007 and 2009. Flexibility decreases with the scale of production, given the significant step-changes in capacity experienced by large airports. Voltes-Dorta and Lei [46] provides both long- and short-run multi-output cost functions estimated from a database of 29 UK airports observed between 1995 and 2009. Interestingly, the paper investigates the case of Manchester Airport. It was de-designated in 2009 and a very strong efficiency incentive was established to achieve a convergence to long-run marginal costs by the end of the period. The principle of matching marginal cost is one of the key ideas for this economic search. It is worth noting that the price charged to airline companies can vary considerably: British Airways pays £6.08 per passenger, MyTravel, JMC, Air2000 and Britannia are charged in the range of £6.55 to £6.71 per passenger, while Ryanair pays only £4.29 per passenger [46]. This should reflect the number of passengers from each company. Marginal cost is also investigated in [47] with respect to airport operations in Norway and a comprehensive review of cost functions in the airport industry is provided by [48], which also presents a detailed real long-run cost function.

In the light of the discussion above, the hypotheses for the model presented here are: The fuel used is a unitary cost $c^{\text{fuel}}$ (€·kg$^{-1}$). The total fuel cost, $C_{\text{fuel}}$, (€) for taxiing is the product of the fuel consumed, $TF$ (kg) and the unitary fuel cost $c^{\text{fuel}}$ (€·kg$^{-1}$), as given in (2). Apart from fuel, the cost of the time for taxiing is a time dependent expense (€·s$^{-1}$) due to the existence of:

- maintenance cost which is time dependent (€·s$^{-1}$), i.e. aircraft maintenance is necessary at defined time intervals.
- aircraft opportunity cost (€·s$^{-1}$). The time spent on taxiing is not used for profitable service.

The total non-fuel aircraft cost $c^{\text{aircraft}}$ (€) is therefore given by (3). The airport opportunity cost $c^{\text{airport}}$ (€·s$^{-1}$) depends on the time of the day (peak vs. off-peak hour), as shown in Fig. 6. With the taxi time defined in seconds, the airport opportunity cost is given in (4). Since all costs are in €, these can be summed and the total cost can then be expressed by (5):

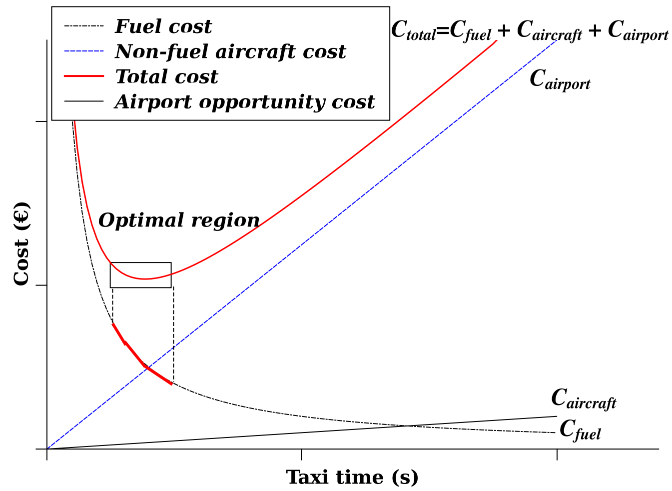
$$C_{\text{fuel}} = c^{\text{fuel}} \cdot TF \tag{2}$$

$$C_{\text{aircraft}} = c^{\text{aircraft}} \cdot TT \tag{3}$$

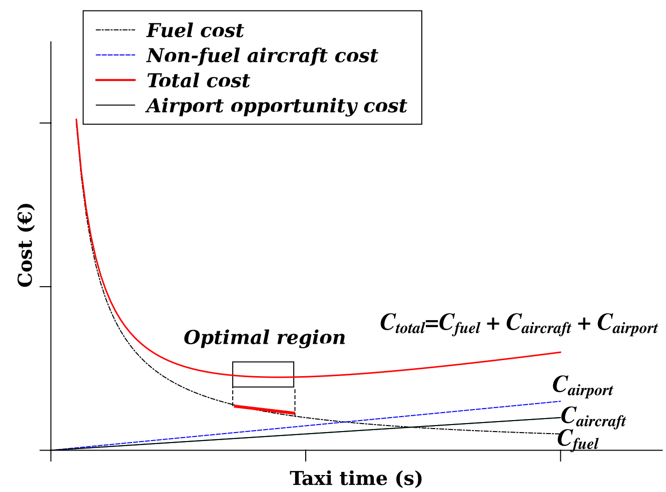
$$C_{\text{airport}} = c^{\text{airport}} \cdot TT \tag{4}$$

$$C_{\text{total}} = C_{\text{fuel}} + C_{\text{aircraft}} + C_{\text{airport}}. \tag{5}$$

Since faster taxi times can increase fuel costs, the resulting function in Fig. 6 shows a trade-off. There are time intervals of minimum cost for each aircraft, which represents the economic solution considering all stakeholders' interests, and these intervals will vary with the load on the airport.




(a) Peak hour.




(b) Off-peak hour.

Fig. 6. Cost search and decision making: (a) fast taxiing is preferred during the peak hour; (b) slow taxiing is preferred during the off-peak hour.

TABLE I
NONFUEL AIRCRAFT COST PER MINUTE OF TAXIING [49]

| Cost scenario | Low | Medium | High |
|---|---|---|---|
| $c^{aircraft}$ (€·min$^{-1}$) | 0.6 | 0.9 | 16.1 |

To illustrate this concept, in this study, we investigate how fuel cost and aircraft cost collaboratively affect decision making with respect to the changing airport environment. A fuel cost of 0.71 €·kg$^{-1}$ (as on 17/01/2014) is used. The non-fuel aircraft cost is assumed to be equal to the delay cost at the gate as in [49] and is a scenario dependent cost as previously discussed. Table I summarizes the aircraft cost with respect to low, medium and high traffic scenarios.

For this work, the airline's perspective is assumed, thus considering only $c^{\text{fuel}}$ and $c^{\text{aircraft}}$. Airport opportunity cost $c^{\text{airport}}$ and the investigation of the way in which it affects the results will be investigated in further work. However, the conclusions drawn in Section V-E still hold without the loss of generality.

TABLE II
INSTANCES

| | Instance | | | | | |
|---|---|---|---|---|---|---|
| | ZRH_L | ZRH_H | ZRH_M | MAN_H | MAN_M | MAN_L |
| Hour | 14:00 – 15:00 | 19:00 – 20:00 | 21:00 – 22:00 | 10:00 – 11:00 | 11:00 – 12:00 | 13:00 – 14:00 |
| Number of aircraft | 21 | 49 | 34 | 21 | 13 | 10 |
| Arrivals | 9 | 33 | 22 | 10 | 5 | 5 |
| Departures | 12 | 16 | 12 | 11 | 8 | 5 |

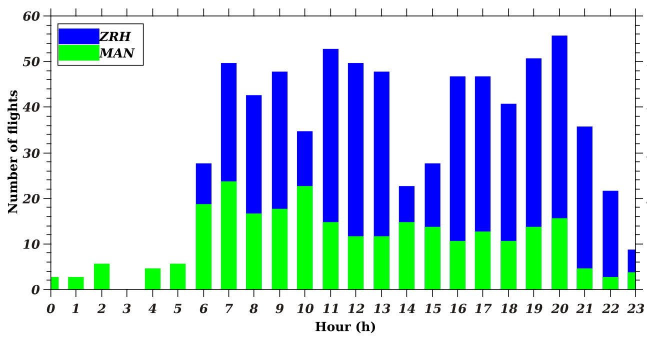



Fig. 7. Number of flights over the given day for ZRH and MAN.

TABLE III
SPECIFICATIONS OF THE REPRESENTATIVE AIRCRAFT

| | Learjet 35A | Airbus A320 | Airbus A333 |
|---|---|---|---|
| Take-off weight $m$ | 8300 kg | 78000 kg | 230000 kg |
| Engines | TFE731-2-2B | CMF56-5-A1 | CF6-80E1A2 |
| Number of engines | 2 | 2 | 2 |
| Rated output $F_o$ | 2×15.6 kN | 2×111.2 kN | 2×287 kN |
| Rolling resistance $F_r$ | 1221 N | 11.48 kN | 33.84 kN |
| Fuel flow at 7% $F_o$ | 0.024 kg·s$^{-1}$ | 0.101 kg·s$^{-1}$ | 0.228 kg·s$^{-1}$ |
| Fuel flow at 30% $F_o$ | 0.067 kg·s$^{-1}$ | 0.291 kg·s$^{-1}$ | 0.724 kg·s$^{-1}$ |

## V. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the proposed AR framework is applied to instances from two busy international hub airports: Zurich Airport (ZRH), Switzerland and Manchester Airport (MAN), United Kingdom.

### A. Description of the Airport Data

The algorithm was tested on a dataset of real arrival and departure flights at ZRH (recorded on 19/10/2007) and MAN (recorded on 11/11/2013). The data has been divided into several instances as summarized in Table II, to give a representation of a typical day, similarly to [19]–[24]. Each instance includes flights departing or landing within one hour, and can be classified into low (L), medium (M), and high (H) traffic according to the current traffic situation on the airport. Fig. 7 shows the number of flights over the given day for ZRH and MAN.

The data for the ZRH instances was provided by the airport and specifies landing/pushback times and gates/runway for each flight. The data for the MAN instances was obtained from publicly available sources [50]. The MAN data has been preprocessed so that noisy (abnormal) data is disregarded and taxiways are automatically assigned by specialized processing tools [51].

In order to keep the problem tractable, aircraft have been divided into 3 groups according to their wake vortex separation requirements (weight category $w_i$). A representative aircraft is designated for each category, and its specifications are used for the calculations of all aircraft within this category. The specifications are summarized in Table III.

### B. Experimental Setup

The routing and scheduling part of the algorithm has been programmed in Java and the speed generation part has been written in the MATLAB programming language. All experiments were carried out on an Intel i3-2120 PC with 3.16 GB of RAM, running Windows 7. In order to empirically derive the most suitable values of $k$ and $p$ (considering both tractability of the problem and fitness of the solutions) as described in Algorithm 1, sensitivity analysis was conducted (see Section V-C). The observations from the sensitivity analysis fed directly into the parameter settings for the computational experiments, and the results in Section V-E were obtained with a setting of $p = 5$ (line 2 in Algorithm 1) and $k = 3$ (line 4) for the $k$-QPPTW algorithm. Similarly to [17], the number of generations for the PAIA based speed profile generation was Gen = 40.

### C. Parameter Analysis

As described in Section III-A, the proposed $k$-QPPTW (Algorithm 1) introduces two parameters: $k$ (the number of generated $k$-shortest routes) and $p$ (the number of discretized points on the Pareto front), which help to keep the problem tractable. As the values of these two parameters not only affect the tractability of the problem but also fitness of the solutions, sensitivity analysis is conducted in this section to justify the choice of the parameter settings used in Section V-E. The appropriate value of $k$ was investigated by running experiments for the three different ZRH instances included in Table II. The parameter $k$ was varied from 1 to 10. In theory, fewer shortest routes mean a more constrained search space, and hence a lower probability of finding better solutions. Since the number of arrival/departure aircraft varied for the different ZRH instances, the calculated $TT$ (total taxi time) and $TF$ (total fuel consumption) also varied. In order to more clearly show the performance of the $k$-QPPTW algorithm against different $k$ values across different instances, the baseline solutions defined as 100% were obtained using $k = 1$. Solutions corresponding to other values of $k$ are then reported as the percentage with respect to the baseline solutions. The results are shown in Fig. 8.

Fig. 8 confirms that with bigger values of $k$, both time and fuel efficiency are improved, meaning that better solutions are found. For ZRH_M, such improvement is still notable even when $k = 10$. However, the most sharp improvement for all three instances happened when $k = 3$.

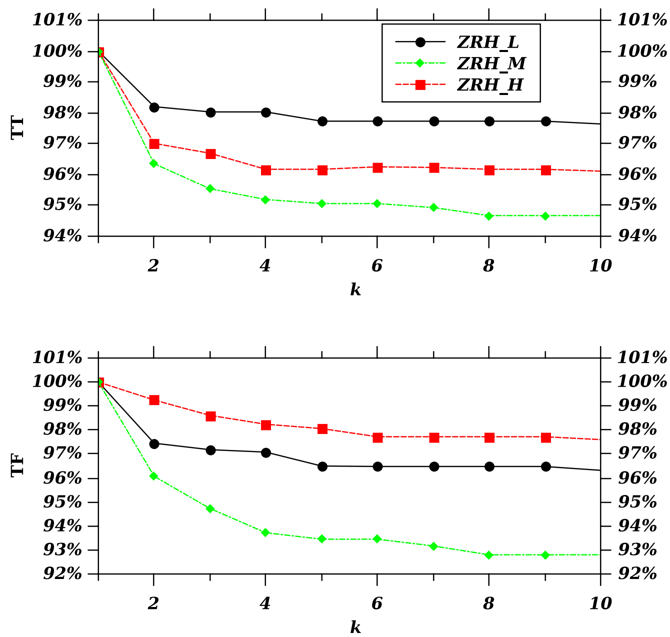



Fig. 8. Minimum taxi time (top) and fuel consumption (bottom) obtained with different $k$, as compared to the baseline solution (100%) with $k = 1$.

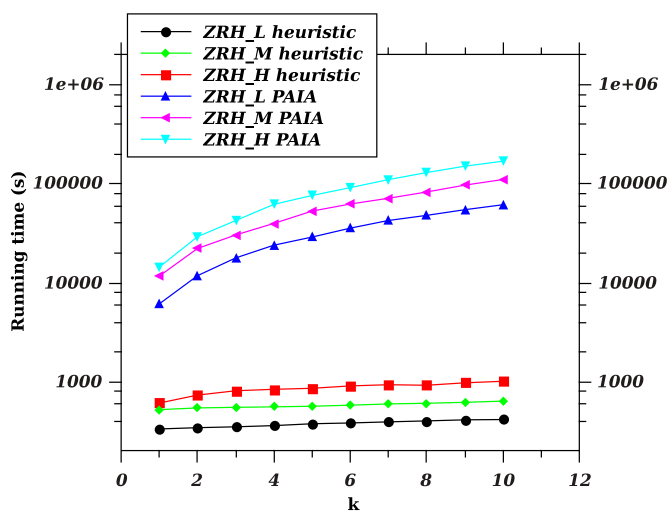



Fig. 9. Comparative run times for differing data sets and speed profile generation algorithms.

Considering the tractability of the problem, the running time against different values of $k$ was also investigated, and the results are shown in Fig. 9.

As PAIA based speed profile generation [16] is the most computational expensive part of the $k$-QPPTW algorithm, the runtime increases accordingly as $k$ is increased. Therefore, $k = 3$ was selected as a good compromise between tractability and fitness of the solutions for the following experiments. The heuristic speed profile generation approach [16] improves the computational efficiency of $k$-QPPTW considerably, as the most time consuming elements of the PAIA algorithm are no longer used and the decision variable space is much reduced. However, it is worth mentioning again, as explained in [16], that despite the greatly improved search speed efficiency, the heuristic approach may not be feasible when more generalized speed profiles, more realistic aircraft performance models, and more objectives are considered.

$p$ was set to 5 in the above parameter analysis. From Algorithm 1, it can be concluded directly that the runtime due to different values of $p$ is a multiple of the corresponding runtime due to $k$. Therefore, $p$ was set to 5 to provide sufficient trade-off solutions for the economic search and decision making without sacrificing too much computational efficiency.

### D. A Heuristic Airport Ground Movement Simulator

As discussed in [16], the previous research on airport ground movement can be classified into the 1st and 2nd generations, which use empirically determined constant speed or predicted constant speed, respectively. The AR framework can be said to represent the 3rd generation, and a comparison between the approaches would be interesting. Previously, routing and scheduling were based on constant speeds (or bounds) without any consideration of how this would impact on the real operational scenario. In practice, instructions to pilots which were based on time constraints may need to be violated due to acceleration/deceleration characteristics and physical speed constraints. Furthermore, fuel consumption estimation which assuming an average thrust setting will be inaccurate since the real speeds will differ from the assumed constant speed.

In order to provide a fair comparison of these different approaches, a heuristic ground movement simulator is introduced in this section for the 1st and 2nd generation approaches to mimic the behavior of pilots who try to follow the given instructions, taking into account acceleration and physical speed constraints. The instructions are represented by a set of timings associated with nodes, determining the traversal time of aircraft along edges. Trying to comply with these timings in the best possibly way will minimize $TW_e$ violations. The simulator re-creates the speed profile with acceleration/deceleration and constant speed phases, trying to comply with these timings. At the beginning of each edge, the aircraft accelerates/decelerates from speed $v_0$ with the maximum acceleration/deceleration rate $a_{\max} = \pm 0.98\ \mathrm{m \cdot s^{-2}}$ (as per the heuristic speed profile generation approach [16], this is the most time and fuel efficient way of taxiing) for $t_1$, until it reaches speed $v_2$ as given in (6). It then continues at speed $v_2$ until the end of edge $e$ for $t_2$. Time $t_2$ is calculated using remaining time $t_e^{\mathrm{rem}}$ for edge $e$ to meet the timing as given in (7). The speed $v_2$ at the end of the edge $e$ is calculated from (8) since the distance traveled during acceleration/deceleration and constant speed phases has to be equal to the total distance $d_e$ of edge $e$. As in [16], maximum speed constraints are applied respectively for straight or turning segments. Moreover, the simulator bounds $v_2$ to such a value that it is still feasible to break (with rate $a_{\max}$) to reach the nearest turning/holding segment at an acceptable speed

$$t_1 = \frac{v_2 - v_0}{a_{\max}} \tag{6}$$

$$t_2 = t_e^{\mathrm{rem}} - t_1 \tag{7}$$

$$v_0 \cdot t_1 + \frac{1}{2} \cdot a_{\max} \cdot t_1^2 + v_2 \cdot t_2 = d_e. \tag{8}$$

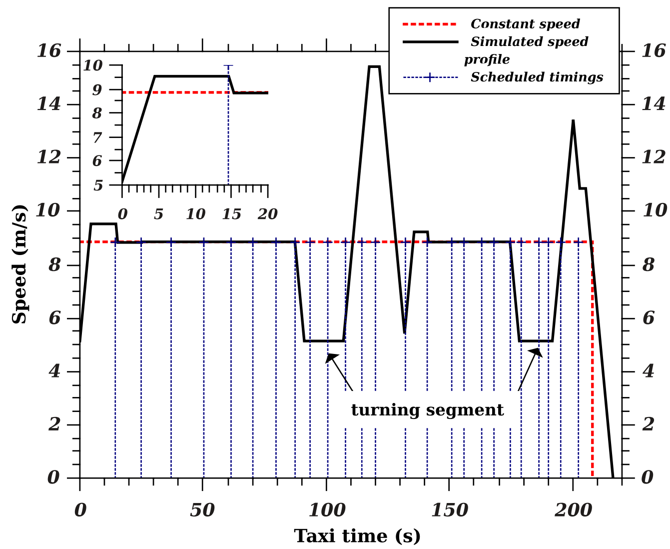



Fig. 10. Simulated speed profile for scheduling based on constant speed.

Fig. 10 illustrates one example of re-creating a realistic speed profile for an arriving aircraft. In this case, the routing and scheduling is based on the 2nd generation approach, where the taxi speeds are predicted using statistical methods [52].

At the start (0 s), the aircraft exits the runway with the actual speed $v_0 = 5.14\ \mathrm{m \cdot s^{-1}}$. It has to accelerate in order to meet the first timing given by the scheduling. The simulator aims to reach as high speed $v_2$ as possible, then to stay at $v_2$ for the rest of the first edge. In doing so, the period spent on $v_2$ (the largest source of fuel burn) and the total taxiing time for this edge are reduced. Therefore, the re-created speed profile assumes the most time and fuel efficient way of following the instructions and provides upper bounds for comparison with the proposed AR framework. After the first timing (edge), the speed has to be reduced back to the instructed (assumed) constant speed of $8.86\ \mathrm{m \cdot s^{-1}}$. Otherwise, the aircraft will arrive at the following edges ahead of the instructed timings. Until time 90 s, the aircraft can comfortably meet the timings by taxiing with the given constant speed. However, for turning at time 100 s, the aircraft has to reduce its speed to the turning speed. As a result, for the subsequent edges, the aircraft has to accelerate to catch up with the delay caused by turning. The delay is successfully eliminated at time 140 s. The similar situation repeats for turning at time 190 s. Finally, the end of the route is reached with a small delay around 10 s.

### *E. Results*

In this section, the proposed AR framework is compared with the 1st and 2nd generation approaches in terms of the total taxi time and fuel consumption, the realism of the produced taxiing planning, the average thrust settings, and planned efficient routes. The 1st and 2nd generation approaches are based on QPPTW [22]. The 1st generation approach is based on the assumed constant speed: $8\ \mathrm{m \cdot s^{-1}}$ for straight segments and $5.14\ \mathrm{m \cdot s^{-1}}$ for turns, according to [19]. The 2nd generation is based on the predicted speed using the statistical method [52]. Cost-effective results are derived using the AR approach (the 3rd generation).

*1) Comparison of the 1st, 2nd, and 3rd Generations:* Tables IV and V show comparative results for the 1st, 2nd and 3rd generation approaches using the real data. For the real data, as it does not provide aircraft detailed positions, detailed discrimination of different taxi phases could not performed. Therefore, fuel burn is estimated using: a) the calculated thrust based on the averaged constant speed from the data; b) the assumed averaged thrust of 5% according to [8]; and c) the assumed averaged thrust of 7% according to [53]. Fuel burn estimations for the 1st and 2nd generation approaches are obtained using the simulated speed profile given by the simulator. For the 3rd generation approach, results are obtained using both the PAIA and heuristic based speed profile generation methods. The fuel burn is estimated using the corresponding fuel flow from the ICAO engine emissions database as detailed in [16].

It can be seen from the results that the 1st generation approach is sensitive to the assumed constant speeds. Setting up appropriate speeds is a prerequisite to gaining improvements in airport operational performance. Appropriate speeds are not only airport dependent, but also scenario dependent. For example, in the cases of ZRH_M and ZRH_H, using the 1st generation approach did not improve either time or fuel efficiency with respect to the real data. This is due to the assumed constant speeds for these two scenarios being lower than the actual speeds calculated from the real data. For ZRH, the scheduled taxi times using the 1st generation approach are higher than those of the 2nd generation approach for all instances, while for MAN, it is the opposite. That is, the assumed constant speed is underestimated for ZRH compared to the recorded speeds, but overestimated for MAN. Such observations are also evident in Table V (the 2nd and 3rd rows). The 2nd generation approach improves the airport efficiency with respect to the real data, since the predicted speeds take into account the airport configuration and the real operational practice. Therefore, the 2nd generation approach is more realistic than the 1st generation approach. However, it is worth pointing out that the 2nd generation approach is based on the predicted speeds, i.e., past experiences. Therefore, for MAN, as the predicted speeds are lower than the assumed constant speeds used in the 1st generation approach, the efficiency is inferior to those of the 1st generation approach. It is argued here that one of the objectives of using decision support tools is to explore any potential benefits that may be gleaned from different practices and review the current regulations. The 2nd generation approach confines its search space and may miss potential benefits unless the current behavior changes. Simulated taxi times introduce delays for all instances, due to unrealistically instructed speeds not considering detailed acceleration/deceleration and physical constraints.

Comparisons between the 3rd and the first two generation approaches show the superiority of using the proposed AR framework. Table IV provides two extreme solutions from the approximate Pareto optimal solution set. In all cases, both fuel and time efficiency have been greatly improved. The most fuel efficient solution gives the most time inefficient taxiing. However, these are still considerably less than those of the real data,

TABLE IV
DETAILED SAVINGS IN TIME AND FUEL AS A RESULT OF EMPLOYING THE AR

| | | Instance | | | | | |
|---|---|---|---|---|---|---|---|
| Algorithm | Objective | ZRH_L | ZRH_M | ZRH_H | MAN_L | MAN_M | MAN_H |
| Real data | Actual taxi time (s) | 8165 | 9672 | 17377 | 5073 | 9225 | 15147 |
| | Time per aircraft (s) | 389 | 284 | 355 | 507 | 710 | 721 |
| | Fuel (calculated thrust based on constant speed) (kg) | 1401 | 1660 | 2982 | 871 | 1776 | 3137 |
| | Fuel (Average thrust 5%) (kg) | 1380 | 1634 | 2936 | 857 | 1722 | 3015 |
| | Fuel (Average thrust 7%) (kg) | 1649 | 1954 | 3510 | 1024 | 2070 | 3636 |
| 1st gen, constant speed | Scheduled time (s) | 6334 | 10800 | 18010 | 3258 | 4686 | 8109 |
| | Simulated time (s) | 6452 | 10923 | 18255 | 3278 | 4727 | 8167 |
| | Time per aircraft (s) | 307 | 321 | 373 | 328 | 364 | 389 |
| | Simulated fuel (kg) | 1266 | 2113 | 3540 | 678 | 1126 | 1990 |
| 2nd gen, predicted speed | Scheduled time (s) | 6299 | 8131 | 13586 | 3823 | 5184 | 8793 |
| | Simulated time (s) | 6495 | 8755 | 14403 | 3848 | 5216 | 8901 |
| | Time per aircraft (s) | 309 | 258 | 294 | 385 | 401 | 424 |
| | Simulated fuel (kg) | 1313 | 1945 | 3143 | 738 | 1185 | 2190 |
| AR (PAIA) | AR time (most time efficient) (s) | 3456 | 5851 | 9408 | 1614 | 2847 | 4893 |
| | Time per aircraft (s) | 165 | 172 | 192 | 161 | 219 | 233 |
| | AR time (most fuel efficient) (s) | 3776 | 6538 | 10468 | 1798 | 3178 | 5503 |
| | Time per aircraft (s) | 180 | 192 | 214 | 180 | 244 | 262 |
| | AR fuel (most time efficient) (kg) | 1004 | 1692 | 2673 | 480 | 968 | 1682 |
| | AR fuel (most fuel efficient) (kg) | 885 | 1479 | 2423 | 413 | 832 | 1460 |
| AR (Heuristic) | AR time (most time efficient) (s) | 3425 | 5850 | 9440 | 1614 | 2844 | 4909 |
| | Time per aircraft (s) | 163 | 172 | 193 | 161 | 219 | 234 |
| | AR time (most fuel efficient) (s) | 3915 | 6719 | 10689 | 1867 | 3249 | 5618 |
| | Time per aircraft (s) | 186 | 198 | 218 | 187 | 250 | 268 |
| | AR fuel (most time efficient)(kg) | 1033 | 1736 | 2754 | 485 | 988 | 1740 |
| | AR fuel (most fuel efficient) (kg) | 895 | 1487 | 2426 | 417 | 841 | 1478 |

TABLE V
AVERAGE THRUST SETTINGS

| | Instance | | | | | |
|---|---|---|---|---|---|---|
| Algorithm | ZRH_L | ZRH_M | ZRH_H | MAN_L | MAN_M | MAN_H |
| Constant speed | 5.16 | 5.16 | 5.16 | 5.17 | 5.27 | 5.23 |
| 1st generation simulated | 6.65 | 6.48 | 6.51 | 7.30 | 7.14 | 7.20 |
| 2nd generation simulated | 7.01 | 8.22 | 7.98 | 6.38 | 6.81 | 6.82 |
| AR (PAIA) most time efficient | 12.36 | 12.28 | 11.97 | 12.77 | 12.62 | 12.54 |
| AR (Heuristic) most time efficient | 13.03 | 12.73 | 12.43 | 12.96 | 12.24 | 12.04 |
| AR (PAIA) most fuel efficient | 8.96 | 8.47 | 8.78 | 8.68 | 8.18 | 8.19 |
| AR (Heuristic) most fuel efficient | 8.61 | 8.17 | 8.51 | 8.29 | 8.42 | 8.40 |

and the 1st and 2nd generation approaches. Similarly, the most time efficient solution gives the most fuel inefficient taxiing, but savings in fuel consumption are still obtained. This is largely due to the reduced total taxi times, but also the reduced number of acceleration events, as will be discussed later.

Table V reveals that, perhaps in contrast to "common sense," a slightly higher average thrust setting surprisingly improves both time and fuel efficiency. This observation is only true if the detailed acceleration/deceleration and physical constraints are considered in the thrust settings. This complies with the discussion in Section I. Since efficient speed profile generation methods take into account the acceleration thrust level and its duration beforehand and are seamlessly embedded within the routing and scheduling algorithm, the resulted taxi planning will improve the duration spent on "acceleration" and "taxi at constant speed," the two largest sources of surface fuel consumption. This observation can be clearly observed in Fig. 11, where a comparison of speed profiles generated by the AR (PAIA) and simulated speed profiles based on the 2nd generation approach is given. In this comparison, for the 2nd generation approach, the average speeds are set to those which were calculated using time from the obtained AR speed profiles ($11.22\ \mathrm{m \cdot s^{-1}}$ for the most time efficient and $10.64\ \mathrm{m \cdot s^{-1}}$ for the most fuel efficient) to provide a fair comparison. In both cases, the simulated speed profiles resulted in more time and fuel consumption ($g_1 = 184.2$ s, $g_2 = 50.28$ kg and $g_1 = 191.22$ s, $g_2 = 49.89$ kg, respectively) compared to the AR results ($g_1 = 165.07$ s, $g_2 = 46.90$ kg and $g_1 = 174.11$ s, $g_2 = 42.20$ kg). This is due to the higher number of acceleration/deceleration events and longer constant taxi phase during the first 70 s. Furthermore, from 130 s to the end of taxi, excessive acceleration/deceleration is observed for the simulated speed profiles. Clearly, setting the constant speed to an appropriate value for each segment individually would result in a speed profile similar to the one generated by the AR. However, setting these speeds can be only achieved by searching for the efficient speed profiles, such as using methods in [16], which is at the heart of the AR.

The results given by the simulator (no matter whether it is the 1st or 2nd generation approaches) resemble the research carried out by NextGen [54] to some degree, where efficient speed profiles are generated after the routing and scheduling. However, as the search for efficient speed profiles is carried out in a post processing manner in [54] and constrained by the constant speed assumption in routing and scheduling, results are generally inferior to those from the 3rd generation approach.

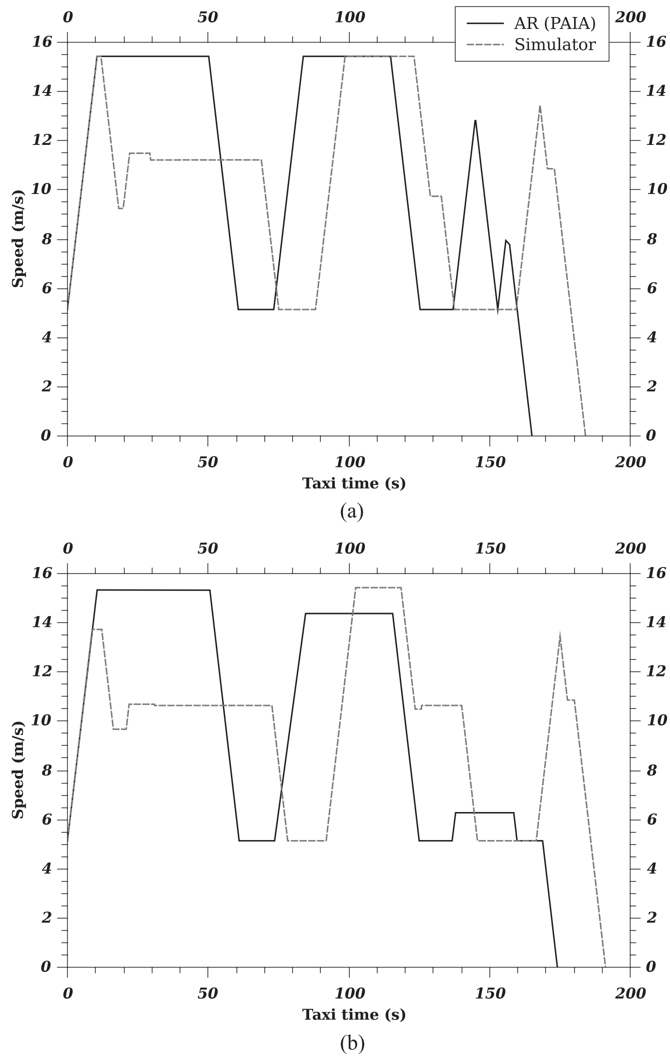



Fig. 11. Comparison of speed profiles generated by AR (PAIA) and simulated second generation: (a) most time efficient and (b) most fuel efficient.

For the 1st and 2nd generation approaches, some timings will be missed due to unrealistic instructions, no matter how hard pilots (the simulator) try to comply with them. Missing timings by only a small deviation from the given instructions may not cause serious problems if the simulated speed still complies with time windows. Time window violations due to unrealistic instructions are more serious, as these will cause conflicts with other aircraft. Table VI summarizes missed timings and time window violations for both the 1st and 2nd generation approaches. This problem is more serious for higher traffic situations and when taxi planning is based on a higher constant speed assumption, as the schedule is normally tighter in these scenarios. For the 3rd generation, as the instruction is based on the detailed speed profiles, assuming perfect execution (this is achievable through automatic control, or the generated speed profile could be relaxed into a speed envelope considering pilot behavior variations), there are no missed timings or violations of time windows.

The results obtained by the 3rd generation approach are comparable to each other. As PAIA produces better speed profiles than the heuristic does, once they are incorporated into the AR framework, the results are also better in terms of both time and fuel efficiency. The running time of the AR (PAIA) is considerably higher than that of the heuristic based approach, as indicated in Table VII. However, as mentioned in [16], the PAIA based approach provides more flexibility to incorporate more objectives and more complex aircraft performance models.

In the AR approach, the planned route of the aircraft can differ from the generated shortest routes due to the time windows imposed by other taxiing aircraft. An example of this scenario is illustrated in Fig. 12.

Similarly, aircraft may not follow the predicted shortest route even if time windows are available. Fig. 13 shows 3 example routes from ZRH. For the predicted shortest route [Fig. 13(a)], the most time efficient speed profile is ($g_1 = 178$ s, $g_2 = 56$ kg), whereas the most fuel efficient one has ($g_1 = 206$ s, $g_2 = 47$ kg). The fastest route is shown in Fig. 13(b) with ($g_1 = 173$ s, $g_2 = 54$ kg). The fastest route is quicker than the predicted shortest route due to shorter turns. The most fuel efficient route is illustrated in Fig. 13(c) with ($g_1 = 193$ s, $g_2 = 44$ kg). The lower fuel consumption is caused by a lower number of segments compared to the shortest route and thus fewer accelerations. Specifically, the most fuel efficient route has only 3 turning segments compared to 4 in the case of the shortest route. In the current implementation of the AR framework based on the $k$-shortest path approach, the predicted shortest route is dominated by the fastest and the most fuel efficient routes. Therefore, it is discarded. Depending on the operational period, as will be discussed in the next section, the fastest and the most fuel efficient routes will be selected and one of the feasible speed profiles for these two routes complying with all of the time windows will be adopted. In the worst case scenario, if no speed profiles for these two routes are feasible, an extra holding time will be added to all speed profiles until time windows are again available. It is worth pointing out that, in this case, the discarded predicted shortest route may provide better solutions. This is one of the drawbacks of using the $k$-shortest path approach. Future study is needed to investigate other MSPP approaches to better address this problem.

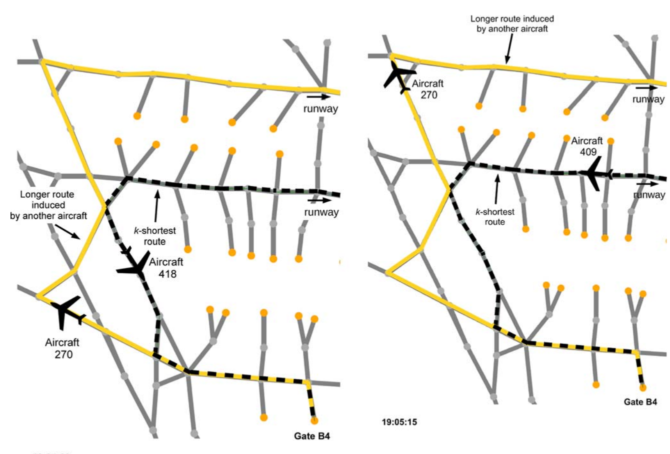
*2) Decision Making and Cost-Effective Operation:* As discussed in Section IV, many factors have to be considered when it comes to decision making: a) different interests among the stakeholders; b) different operational periods; and most importantly c) the cost implications of such a choice. The proposed conceptual economic search framework fulfills these considerations. Although in this paper, results only consider airlines' interests and different operational periods, airports' interests will be readily accommodated once the coefficient $c^{\text{airport}}$ is properly derived. Fig. 14 shows Pareto fronts after routing and scheduling using the $k$-QPPTW algorithm for ZRH_H and MAN_L. As $c^{\text{aircraft}}$ is scenario dependent, different strategies to route and schedule aircraft are adopted for different operational periods. During busier times, aircraft taxi more rapidly, which burns fuel more inefficiently but places an emphasis on shorter taxi time. Conversely, during quieter times, aircraft taxi less rapidly, placing an emphasis on more efficient fuel consumption.

TABLE VI
RESULTS FOR SIMULATOR

| | | Instance | | | | | |
|---|---|---|---|---|---|---|---|
| Algorithm | Metric | ZRH_L | ZRH_M | ZRH_H | MAN_L | MAN_M | MAN_H |
| 1st gen, constant speed | Delay per A/C (s) | 6 | 4 | 5 | 2 | 3 | 3 |
| | Missed timings | 38% | 25% | 35% | 28% | 31% | 30% |
| | Violated time windows | 0 | 0 | 3 | 0 | 0 | 0 |
| 2nd gen, predicted speed | Delay per A/C (s) | 9 | 18 | 17 | 2 | 2 | 5 |
| | Missed timings | 30% | 59% | 49% | 25% | 35% | 38% |
| | Violated time windows | 0 | 0 | 9 | 0 | 0 | 0 |

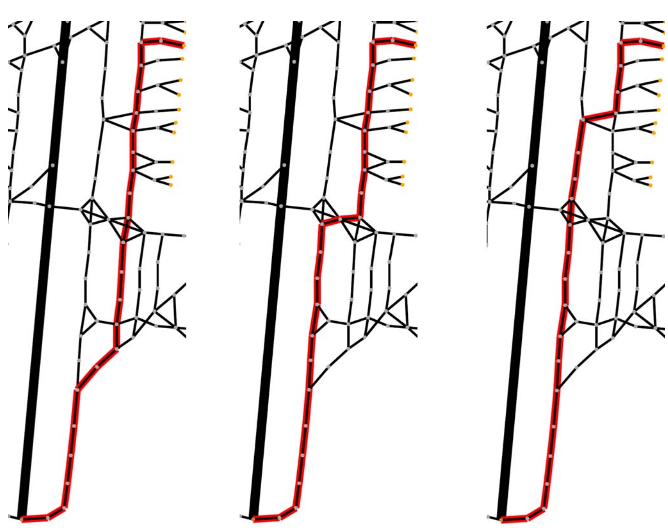
TABLE VII
RUNNING TIMES OF ALGORITHMS (IN MINUTES)

| | Instance | | | | | |
|---|---|---|---|---|---|---|
| Algorithm | ZRH_L | ZRH_M | ZRH_H | MAN_L | MAN_M | MAN_H |
| AR (PAIA) | 243 | 382 | 606 | 132 | 219 | 332 |
| AR (Heuristic) | 5 | 7 | 13 | 4 | 4 | 6 |




(a) (b)

Fig. 12. Snapshot of aircraft 270 taking a longer route (solid line) compared with the $k$-shortest route (dashed line) due to time window constraints induced by two other aircraft.



(a) (b) (c)

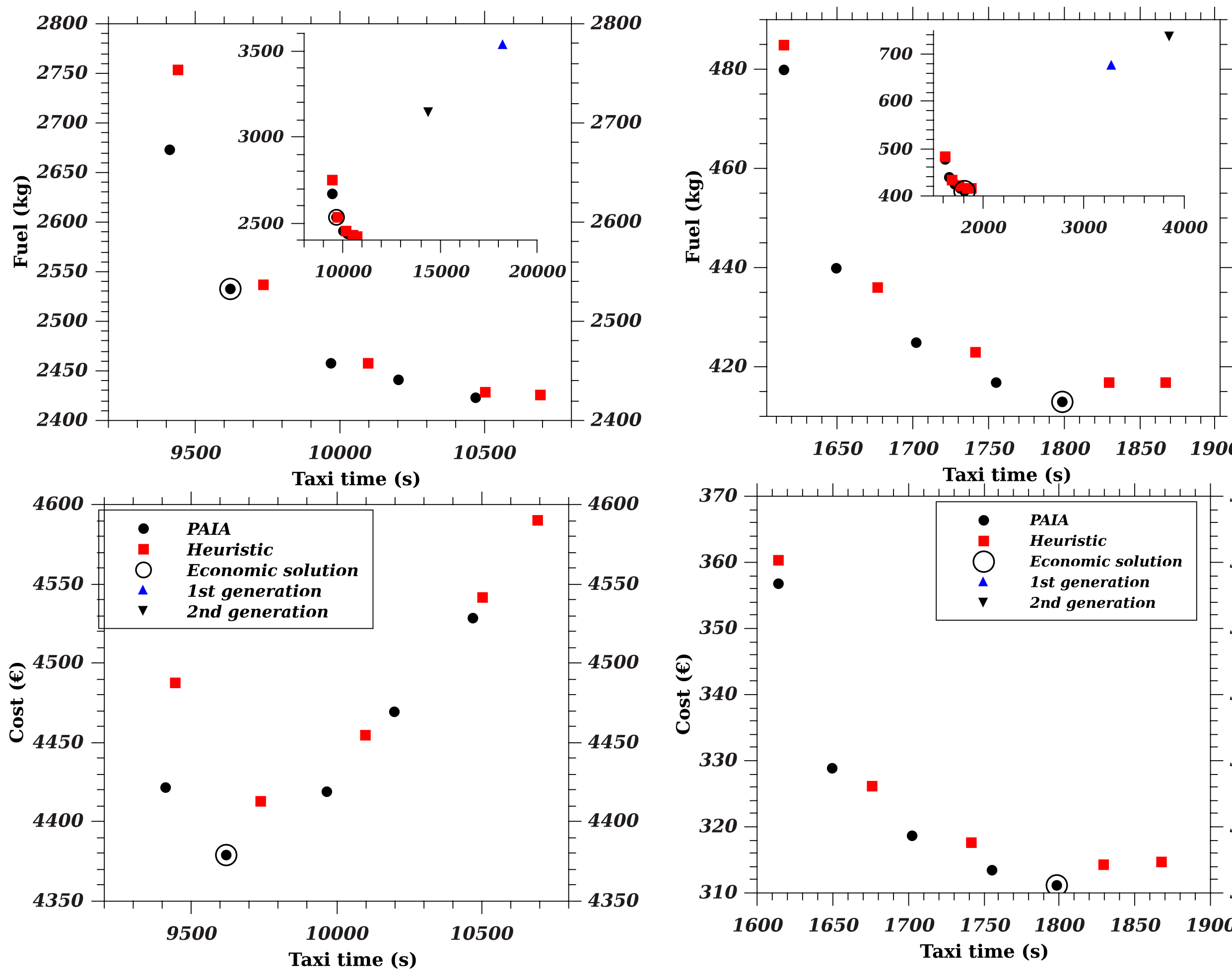
Fig. 13. (a) Shortest route in terms of constant speed, (b) the fastest, and (c) the most fuel efficient.

Table VIII summarizes the detailed potential savings in both time and fuel by deploying the economic search results. The results are compared with the 1st and 2nd generation approaches. Due to the more realistic speed for routing and scheduling, both time and fuel efficiency have been greatly improved. Savings in fuel consumption for MAN are greater than ZRH using the AR framework. This is due to the fact that MAN has more turning segments than ZRH. Unlike the 1st and 2nd generation approaches, improved speed profiles take this factor into account. However, the extra accelerations and decelerations are required in the simulated speeds for the 1st and 2nd generation approaches, hence more fuel consumption. This indicates that more benefit will be gained using the proposed AR framework for airports with a more complex layout.

## VI. CONCLUSION

In this paper, a new holistic Active Routing framework is introduced for efficient airport ground operations. The framework seamlessly integrates the multi-objective speed profile generation approach proposed in [16], the MSPP based on the $k$-shortest path approach, and the economic search framework. The contributions of this paper are summarized below:

1) The proposed framework provides a systems approach for benefit assessment of the speed profile (trajectory) based air traffic management concept.
2) A detailed comparison of the current operations, the 1st, 2nd and 3rd (the proposed AR framework) generation approaches. Great improvement in both time and fuel efficiency have been achieved using the proposed AR approach. This is due to adopting more realistic speed profiles within the routing and scheduling function.
3) A higher thrust setting during the acceleration phase is suggested as this will reduce the "taxi at constant speed" phase and the overall taxi times, hence the fuel burn. This will only cause a slight increase in the overall average thrust level. However, this claim is only true




(a) (b)

Fig. 14. Global Pareto front (top) and corresponding economic cost (bottom) for (a) ZRH_H and (b) MAN_L.

TABLE VIII
ECONOMIC SEARCH RESULTS

| Algorithm | Metric | ZRH_L | ZRH_M | ZRH_H | MAN_L | MAN_M | MAN_H |
|---|---|---|---|---|---|---|---|
| Actual time and 5% avg thrust | $C_{total}$ (€) | 1061 | 1305 | 6747 | 659 | 1361 | 6205 |
| 1st generation simulated | $C_{total}$ (€) | 963 | 1664 | 7412 | 514 | 870 | 3604 |
| 2nd generation simulated | $C_{total}$ (€) | 997 | 1512 | 6096 | 562 | 920 | 3943 |
| AR with econ. search | $C_{total}$ (€) | 666 | 1148 | 4380 | 311 | 638 | 2452 |
| | Economic solution time (s) | 3776 | 6538 | 9617 | 1798 | 3178 | 5012 |
| | Time per aircraft (s) | 180 | 192 | 196 | 180 | 244 | 239 |
| | Saving w.r.t. actual taxi time | 54% | 32% | 45% | 65% | 66% | 67% |
| | Saving w.r.t. 1st gen time | 41% | 40% | 47% | 45% | 33% | 39% |
| | Saving w.r.t. 2nd gen time | 42% | 25% | 33% | 53% | 39% | 44% |
| | Economic solution fuel (kg) | 885 | 1479 | 2534 | 413 | 832 | 1559 |
| | Saving w.r.t. 5% fuel | 36% | 9% | 14% | 52% | 52% | 48% |
| | Saving w.r.t. 1st gen fuel | 30% | 30% | 28% | 39% | 26% | 22% |
| | Saving w.r.t. 2nd gen fuel | 33% | 24% | 19% | 44% | 30% | 29% |

when the efficient speed profile is searched beforehand. Otherwise, unnecessary deceleration will follow and fuel efficiency will not be gained. The maximum acceleration thrust should take passenger comfort and safety issues into consideration. The value chosen in this paper is according to [55]. Airports are thus advised to review their current practice with respect to the solutions given by the AR. It is argued that decision support tools should be able to explore practices that have not been widely used before to allow more room for efficiency improvement.

4) Airport ground operations involve many stakeholders with various interests. Furthermore, the airport operational environment changes during the day. The proposed conceptual economic search framework can capture these various changes and provide the most cost-effective solution that will be more easily accepted and tailored to the current operational scenario.

The proposed AR framework also paves the way for a number of further research developments:

1) For the airport ground operations research: a) Nonlinear aircraft ground movement behavior should be properly modeled as this will define the generated speed profiles. b) Different taxiing behaviors, including single and double engine taxiing, and pilot behaviors such as braking with/without reducing the thrust settings, should be considered in the speed profile generation, and routing and scheduling function. c) More objectives, such as emissions and noise, should be included in decision making as these will affect decisions regarding airport regulations. d) More constraints such as the time for aircraft engines to spool up, and various uncertainties, should be considered either in speed profile generation, or in the routing and scheduling. e) Constraint handling mechanisms deserve more investigation, since infeasible speed profiles are currently discarded and holding is applied only when no feasible speed profiles are found, however it might be beneficial to keep infeasible speed profiles and apply different holding times to them. f) Currently, calculating the efficient speed profiles and integrating them into the routing and scheduling is extremely computational demanding and is not suitable for on-line decision support, thus it is worth exploring some pre-processing techniques to reduce the complexity of the airport taxiway layout so that complete efficient speed profiles for this reduced set can be pre-calculated and stored in a database; this is envisioned as the key to bring the proposed AR framework up to on-line decision support. The preliminary results in [56] using such an approach indicate that fast computational time is achievable. g) There is currently a lack of accurate fuel estimation models for airport ground operations, however, with the aircraft engine performance data and fuel consumption data logged by airlines through the flight radar recorders, the proposed AR framework could be calibrated and serve as the airport ground fuel estimation tool. h) As the generated speed profiles consider taxiway configurations, the proposed AR framework could also be employed to search for the optimal airport layout.
2) The problem addressed in this paper also imposes several challenges for MSPP research, especially for the fully connected and directed multigraph problem: a) As any two connected nodes have multiple parallel edges, the search space becomes enormously large and the problem becomes intractable. Although the $k$-shortest path approach has been employed in this paper, setting up a proper value for $k$ is problem dependent and can only be derived empirically. Furthermore, as the $k$-shortest paths are determined based on the constant speed, which is different from any of the realistic speeds, the available $k$ routes and time windows may not provide a good starting point for further search. b) If the definition of the speed profile is relaxed into a speed profile envelope to accommodate variations and uncertainties, the weight matrix pertaining to each edge may become non-additive, therefore, enumerative approaches may not be feasible in this case. Investigation of metaheuristic based MSPP approaches may provide a good solution to such a case. c) Metaheuristic based MSPP approaches may also provide an integrated solution to scheduling so that the solution is not based on the first come first served mechanism.
3) The challenges facing airport ground movement, such as reducing environmental impact due to congestion and inappropriate acceleration, and collaborative decision making within dynamic environment, are also relevant to other modes of public transportation. The proposed AR framework provides a systematic two-level framework and resilient approach in response to such challenges. This is indeed the integrated search method mentioned in [57] which is perceived as the key future technology for energy-efficient train operation for urban rail transit. As mentioned in [57], the aim is to cooperatively maximize the utilization of regenerative energy through synchronization of the accelerating/braking actions, and minimize the tractive energy consumption through the optimized speed profile. Energy-efficient speed control of an individual electric vehicles also demonstrated significant energy saving [58]. The authors concluded that future research needs to address how to achieve a system-level improvement. The proposed AR framework will be directly transferable in this case. As the conclusion, although the proposed AR framework is largely for airport ground movement, it will directly impact wider engineering sectors such as transportation, logistics, precision agriculture and automated passenger/freight systems.

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