Transportation Research Part A 166 (2022) 14–40

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Air traffic flow management under emission policies: Analyzing the impact of sustainable aviation fuel and different carbon prices

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ARTICLE INFO

Keywords:
Green aviation
Sustainable aviation fuel (SAF)
Carbon price
Emission policy
Air traffic flow management (ATFM)

ABSTRACT

As part of the global efforts to make aviation activities more environmentally friendly, the worldwide goal is to achieve a 50% reduction in the 2005 emissions by 2050. In this context, aviation emissions represent a critical challenge to aviation activities, especially with the increasing travel demand up to the beginning of the COVID-19 crisis, starting in 2020. One of the potential drivers that would help the aviation industry reduce its emissions is the use of sustainable aviation fuel (SAF). In this study, we analyzed the impact of SAF from an air traffic flow management (ATFM) perspective, considering delay and re-routing costs. We developed an optimization model that considers, in addition to the traditional ATFM costs, fuel costs and carbon dioxide emissions. We investigated the impact of accounting for these two new aspects, that is, fuel costs and emissions, on ATFM performance, and we compared SAF with conventional fuel. The analysis of a real case study revealed that, in addition to delay and re-routing costs, fuel cost should be included in the ATFM model so that the resulting solution becomes economically and environmentally realistic for airlines. The increase in the fuel cost and network delays when using SAF requires setting an appropriate carbon price under an emission policy, such as the carbon offsetting and reduction scheme for international flights policy, to make SAF more attractive. Furthermore, flexible re-routing programs for flights operated using SAF make it advantageous from an ATFM perspective.

1. Introduction

Although the COIVD-19 pandemic brought had a negative impact on humanity, it benefited the environment with a daily global carbon dioxide (CO_2) reduction of 17% during April 2020 compared to 2019 mean data (Le Quéré et al., 2020). Aviation contributes with around 2.8% of the global fossil CO_2 emissions. Le Quéré et al. (2020) estimated an aviation emission reduction of 60% during the pandemic and the travel restriction period compared to the pre-COVID-19 period. This reduction accounts for around 1.7 $MtCO_2$ per day. Beside CO_2, aviation fuel emits carbon monoxide, sulfate aerosols, nitrogen oxide, water vapor, unburnt hydrocarbons and

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https://doi.org/10.1016/j.tra.2022.09.013
Received 28 October 2021; Received in revised form 17 September 2022; Accepted 21 September 2022
Available online 18 October 2022

Nomenclature

l_j^f	The minimum time allowed for flight f to spend in elementary sector j
$\mathcal{C}$	Set of pairs of flights that are continuing (f, f'), where f represents the flight that will use the same aircraft after the arrival of its preceding flight f'
$\mathcal{F}$	Set of all flights
$\mathcal{K}$	Set of airports
$\mathcal{M}_v$	List of all elementary sectors constituting sector v available in the opening scheme
$\mathcal{P}$	Set of all elementary sectors
$\mathcal{P}_f^z$	Set of elementary sectors that constitute route z of flight f
$\mathcal{P}_f^z(1)$	First elementary sector in the set $\mathcal{P}_f^z$ of flight f in path z
$\mathcal{P}_f^z(j-1)$, $\mathcal{P}_f^z(j+1)$	Preceding and subsequent elementary sectors respectively of the jth elementary sector for flight f in route z
$\mathcal{T}$	Set of discrete time periods. Each period corresponds to 15 minutes
$\mathcal{V}$	Set of all sectors (elementary and collapse) that can be used in the network
$\overline{T}_j^{f,z}$, $\underline{T}_j^{f,z}$	The earliest and latest possible times, respectively, for flight f to enter resource j using route z in the set $T_j^{f,z}$
ψ	Duration of a time period t in hours
φ	A slight super-linear fairness coefficient
$a_f^{j,z}$	Scheduled arrival time for flight f in resource j using route z
C_{cancel}^f	Cost of canceling flight f
C^{CAF}, C^{SAF}	The CAF and SAF fuel prices [€/L]
$C_{reroute}^{f,z}$	Cost of choosing path z for flight f. For the scheduled path $C_{reroute}^{f,z^s} = 0$ [€]
$D_j^{f,z}$	Distance in kilometers spent by flight f in elementary sector j using route z
d_f	Scheduled departure time of flight f
$D_k(t)$, $A_k(t)$	Departure and arrival capacities of airport k at time t
E^{CAF}, E^{SAF}	CO_2 emissions in kg/L of burned fuel for CAF and SAF
$E_v(t)$	Capacity of sector v in the set $\mathcal{V}$ at time t
o_f	The time required for flight f' to spend outside the network before it appears again as flight f in the case of type E flight for each $(f, f') \in \mathcal{F}^E$
$origin_f$, $dest_f$	Departure and arrival airports of flight f
$R_j^{f,z}$	A continuous variables used to indicate the total time spend in a elementary sector j by flight f that uses path z
s_f	The minimum turnaround time needed for flight f to take-off after the arrival of flight f' in the case of continuing flights for each $(f, f') \in \mathcal{C}$
$T_j^{f,z}$	List of possible flight time periods for flight f in resource j, i.e., airport or elementary sector, using path z
T_v^{Sch}	Set of time periods during which sector v is active
$vdest$	Virtual destination airport used to model flights that leave the network or that do not land by the end of the planning horizon
$w_{j,t}^{f,z}$	A binary decision variable that is equal to one if flight f arrives to resource j by time t using path z.
$Y^{f,z}$	A continuous non-negative variable for each flight f in path z used to capture the maximum function's effect used when converting the air delay equation to linear
z^s	The schedule route index
$\mathcal{F}^A$, $\mathcal{F}^B$, $\mathcal{F}^C$, $\mathcal{F}^D$	Flight sets of types A, B, C and D, respectively
$\mathcal{F}^E$	Set of pair of type E flights $(f, f') \in \mathcal{F}^E$, where f represents the second leg of that flight and f' represents the first leg
$\mathcal{Z}_f$	Set of routes belonging to flight f
C_{ground}^f, C_{air}^f	Ground and air delay unit costs, respectively [€/period]

nonvolatile black carbon (soot) (Brasseur et al., 2016; Hamdan et al., 2020; Berger et al., 2022). In addition to the warming effect, some emitted components affect the formation of contrail-cirrus and ozone and methane depletion. For example, contrail-cirrus clouds resulting from aeroplanes affect the atmosphere's solar and terrestrial infrared radiative budget. The climate change impact in 2005 was estimated to be around 5% of the total anthropogenic radiative forcing (RF), including cirrus cloud enhancement (Lee et al., 2010). This estimate is expected to triple or quadruple in 2050 (Lee et al., 2009). Readers may refer to Brasseur et al. (2016), Lee et al. (2009) for further details on the impact of aviation on climate change.

Sustainable aviation fuel (SAF) is a promising environmental solution in the aviation sector as it is expected to achieve a significant emission reduction over its lifecycle compared to conventional aviation fuel (CAF) (International Air Transport Association, 2018; Yang and O'Connell, 2020; Nygren et al., 2009). The emission-reduction ability of SAF depends on its components and the process used. For instance, according to Stratton et al. (2011), SAF produced from soybean oil using the hydroprocessed esters and fatty acids process emits 32%–69% less CO_2 than CAF. In February 2018, the airline industry marked its 10th year anniversary of the first airline flight using SAF. Since then, many commercial airlines began to use SAF during their flights (International Air Transport Association, 2018; Winchester et al., 2013). Aircraft producers have committed to delivering aircraft ready to fly on 100% SAF by 2030. In 2019, approximately 40 million SAF liters were used in over 65,455 flights from two major airports in the United States, two major airports in Norway, and one major airport in Sweden. This amount is less than 1% of the aviation fuel used globally. However, some projects are currently being implemented that will help achieve a 50% reduction in the 2005 emissions by 2050, which will most likely lead to an increase in the use of SAF (International Air Transport Association, 2018; International Civil Aviation Organization, 2019a; FlightPath, 2019).

One of these projects is the carbon offsetting and reduction scheme for international aviation (CORSIA), which is a mitigation and market-measure approach developed by the International Civil Aviation Organization (ICAO). The project aims to address the issue of CO_2 emissions from international flights to achieve carbon-neutral growth beginning from 2020. In this offsetting scheme, airlines in participating states will compensate for their emissions by financing projects through the carbon market to reduce emissions in other sectors. The use of operations management, new technologies, and alternative fuels can help achieve the carbon-neutral objectives of CORSIA (International Civil Aviation Organization, 2019a; Rotaris et al., 2020). Chao et al. (2019) stated that the demand for SAF is expected to increase when the CORSIA policy is implemented. Another project is the Biofuels FlightPath, which is an European industry-wide initiative launched by the European Commission to lead biofuel development and overcome barriers to its deployment. Its primary strategy aims to reduce aviation fuel consumption and, consequently, aviation emissions (FlightPath, 2019).

Because airlines aim to maximize their profits by minimizing their operational costs, fuel costs play a significant role. In 2017, aviation fuel costs accounted for approximately 20% of airline operating costs compared to 30% in 2013 (International Air Transport Association, 2018; Gegg et al., 2014). The 10% difference between the values of 2013 and 2017 is due to a reduction in fuel prices (International Air Transport Association, 2018; European Commission, 2017). One obstacle to using SAF is its high price, which makes CAF more competitive (Pechstein et al., 2020). To overcome this obstacle, governments and policymakers need to set initiatives and policies to make SAF more attractive than CAF (International Air Transport Association, 2018). These initiatives need not only consider the SAF price and its environmental benefits but also account for its impact on the air traffic flow. This is because airlines incur costs not only from fuel but also from how the air traffic flow is managed, that is, delays, slot changing, etc. However, there is a lack of analysis on the impact of SAF from an air traffic flow management (ATFM) perspective, as highlighted in Section 2.

Therefore, in this work, we aim to answer the following main research question (RQ): How will different fuel types affect the ATFM? The main RQ is divided into three secondary RQs (SRQ): (SRQ #1) How does fuel cost (and consequently fuel type) affect the ATFM and the decisions taken? (SRQ #2) What is the trade-off between ATFM costs and emissions, and how does this trade-off change when considering different fuel types/costs? (SRQ #3) Under ATFM constraints, what is the carbon price required under a certain emission policy to make SAF attractive, and will SAF be attractive under the CORSIA policy? Using the Swedish airspace as a case study owing to data availability, we analyze the impact of SAF from the ATFM perspective. We consider a set of airports and their flights in a finite planning horizon. In this setting, airports and airspace sectors have limited capacities (Hamdan et al., 2022b). The proposed model is a bi-objective mixed-integer nonlinear programming model that minimizes the total emissions and cost. Using k-means approach, the Pareto solutions are sorted into three clusters: emission-focused, network-focused, and balanced solutions. Here, by network decisions, we mean the changes from the ATFM perspective, including ground delays, air delays, re-routings, and cancellations. Thus, we do not investigate possible changes in individual airline networks as a result of SAF pricing and emission policies. It is worth noting that the proposed ATFM model considers the strategic airline network design implicitly by considering flight scheduled paths defined by airlines and sets of alternative paths for re-rerouting. In addition, the model considers continuing flights, where an aircraft can perform more than one trip after a specified turnaround period. It also uses the scheduled take-off and landing times and the maximum allowable delays before cancellations.

In addition to addressing the main RQ, we make the following contributions:

- We account for the total cost expressed as a function of flight delays and re-routing penalties, the total fuel cost, and the CO_{2eq} emissions as a function of aircraft speed to optimally manage the air traffic flow network in a bi-objective formulation. Most of the previous studies on ATFM focused only on minimizing network delays.
- We apply the proposed model to a real case study; thus, to obtain a realistic formulation, we consider several flight types that were not considered in the existing literature. In addition, we consider the elementary and collapse sectors (that is, airspace configurations).
- We study the impact of considering the fuel cost on the network's performance in terms of delays and emissions, which has not been previously considered.
- In particular, we investigate the effect of changing the aircraft fuel type to SAF on the performance of the ATFM network and link it to the CORSIA initiative.

- We compare CAF with SAF under different climate policies, such as emission trading, carbon tax and subsidization in the context of ATFM. We investigate the impact of the climate policies on fuel consumption and ATFM network costs. For instance, using some SAFs, such as Synthesized ISO-Paraffins, Alcohol-to-Jet, and a few Fischer–Tropsch (FT) SAFs, results in more fuel consumption savings than a 10%-tax on CAF. Also, when comparing tax on CAF and tax on SAF, it appears that SAF tends on average to reduce consumption more than CAF.

The remainder of this paper is organized as follows. In Section 2, we review related works. In Section 3, we model fuel consumption as a function of speed and discuss the relationship between fuel consumption and emissions. In Section 4, we integrate fuel costs and emissions in the ATFM model. In Section 5, we present the solution approach of the bi-objective optimization model. In Section 6, we provide the extracted managerial insights from the analyzed case. In Section 7, we discuss the policy implications of the proposed model. Finally, in Section 8, we conclude the paper and highlight some future research directions.

2. Literature review

The relevant literature can be classified into five main categories. The first category presents the different fuel consumption modeling attempts, the second category summarizes the several SAF types and production processes, the third category focuses on analyzing the economic and environmental impacts of SAF, whereas the fourth category focuses on ATFM-related works. The last category summarizes works done on analyzing the impact of aviation emissions.

In the first category, fuel consumption estimation is an important input when making strategic and tactical planning decisions. For instance, Collins (1982) calculated the fuel consumption using the energy balance approach. The proposed formula requires mechanical data, such as the aircraft thrust and operational data related to the flight path information. Trani et al. (2004) used a neural network to estimate fuel consumption for the Fokker 100 aircraft and SAAB 2000 aircraft. The developed model uses altitude, weight, speed, and temperature to predict the fuel burn during the climb phase. Senzig et al. (2009) improved the fuel consumption calculation for the terminal area using aircraft performance data. Delgado Muñoz and Prats Menéndez (2009) assessed how speed variation, weight and flight level under a selected cost index affect fuel consumption. They found that the high-cost index allows more speed margin without affecting the fuel consumption. Nikoleris et al. (2011) estimate the fuel consumption during taxiing operation. Zhu et al. (2019) used an improved k-means clustering to determine the best landing altitude and true airspeed based on the fuel consumption. These authors found a positive correlation between aircraft weight and fuel consumption. Baumann and Klingauf (2020) used full-flight data to develop an artificial intelligence model to predict fuel consumption. Huang and Cheng (2022) estimated aircraft fuel consumption from flight data recorder and automatic dependent surveillance-broadcast using neural network and classification and regression tree.

In the second category, one can observe several conversion processes and tests to produce SAF or to validate its suitability. One conversion process is the biomass-to-liquid via the Fischer–Tropsch process, which was approved in 2009 by the American Society for Testing and Materials (ASTM). It converts a mixture of coal and biomass to gas, then, using the FT process, to synthetic liquid fuel (Winchester et al., 2013). Another process is the hydro-processed esters and fatty acids (HEFA) that uses hydrogen treatment for renewable oils. It was approved in 2011 by the ASTM (Winchester et al., 2013). In addition to these two processes, the synthesized iso-paraffins from hydroprocessed fermented sugars (SIP), the synthesized kerosene with aromatics derived by alkylation of light aromatics from non-petroleum sources (FT-SKA), the alcohol to jet synthetic paraffinic kerosene (ATJ-SPK), and the co-processing of fats, oils, and greases (FOG) in a traditional petroleum refinery processes were also approved by the ASTM and are suitable as aviation fuel alternatives and for the use under CORSIA scheme (International Civil Aviation Organization, 2019b). Other conversion processes are being reviewed, such as high freeze point HEFA, bioForm synthesized kerosene jet fuel, and LanzaTech ATJ-SPK (Ethanol to Jet) (Zhang et al., 2020). Various feedstocks, such as agricultural residues, woody crops, animal fats, vegetable oil, municipal solid waste and corn grain, can be used in the conversion process resulting in a fuel with different characteristics. Zhang et al. (2020) discussed the opportunities and challenges facing SAF. They concluded that lignin-derived jet fuel could improve the economic viability of SAF due to its low-cost production, high thermal stability and energy density and low greenhouse emissions. Heyne et al. (2021) outlined the prescreening procedures for SAF before the official ASTM evaluation process to reduce the costly correction efforts. Readers can refer to Zhang et al. (2020), International Civil Aviation Organization (2019b) for further details about the conversion procedure and properties of different SAF pathways.

Silitonga et al. (2016) evaluated the properties of fuel produced from crude palm and Calophyllum inophyllum oils. They found that oxidation stability for more than 12 h is maintained after storing the biofuel in vacuum chambers for 90 days, which aligns with the standards. Ranucci et al. (2018) described the process of obtaining SAF from the transesterification and subsequent distillation of jatropha, babassu, and palm kernel oils. Peiffer et al. (2019) focused on analyzing low-cost SAF screening tools required for the fuel approval process by combining timescale theory with reduced-order fuel properties and random forest regressions. Karkal and Kudre (2020) reviewed and compared SAF production methods using fish discards.

In the third category, Murphy et al. (2015) assessed the economic factors and sustainable issues related to biomass production in Queensland. The authors reported that Queensland is capable of producing sufficient biomass to support a hypothetical industry scale-up. Hayward et al. (2015) extended the work of Murphy et al. (2015) by providing production costs and detailed cost analysis. Meanwhile, González and Hosoda (2016) investigated the impact of fuel tax reduction on CO_2 emissions. Filimonau et al. (2018) surveyed public opinion on the use of SAF in aviation and reported low awareness levels regarding the challenges, technologies, and safety aspects. Lu (2018) conducted a cost–benefit analysis of CAF and SAF in selected flight routes. The results of the study revealed that SAF is viable under very high environmental costs or when the price of SAF is 8%–11% higher than that of CAF. Chao et al. (2019) used Monte Carlo simulation and lifecycle analysis (LCA) to assess the impact of two CORSIA policy scenarios on SAF consumption and emissions in the United States. Their results showed that CORSIA could reduce emissions by 37.5%–50% in 2050 with a probability of 3.5% and that carbon and fuel prices are the most critical factors for the policy success. Chen and Ren (2018) compared four fuel alternatives using a fuzzy analytic network process and fuzzy gray relational analysis. Wang et al. (2019) assessed the socioeconomic impact of SAF in Brazil by studying its effect on trade balance and employment. The results revealed that SAF positively impacted employment and negatively impacted the fossil fuel sector. Staples et al. (2018) assessed emission levels when using SAF and concluded that approximately 68% reduction could be achieved in 2050; however, this would require offsetting more than 85% of the aviation fuel demand with SAF. Pechstein et al. (2020) presented a methodology for including SAF in the European Emissions Trading System using the book-and-claim principle. They suggested that, in addition to its flexibility and marketing benefits, the book-and-claim approach might be suitable for CORSIA to account for the use of SAF.

In the fourth category, several studies have focused on ATFM network features such as ability to re-route flights (Bertsimas and Patterson, 1998; Hamdan et al., 2018, 2022a), late and early arrivals (Agustín et al., 2012), airport capacity dependency (Boujarif et al., 2021b), delay duration impact (Boujarif et al., 2021a), fairness in delay distribution among flights (Lulli and Odoni, 2007; Andreatta et al., 2011), limiting the total reversals (Hamdan et al., 2018; Bertsimas and Gupta, 2015; Hamdan et al., 2022a), slot allocation (Ivanov et al., 2017), equity (Erkan et al., 2019), utilization (Yun-xiang et al., 2019), and accounting for waypoints (García-Heredia et al., 2019). Moreover, several studies have discussed the stochastic nature of capacity (Chen et al., 2017; Alonso et al., 2000). Recently, Akgunduz and Kazerooni (2018) considered the total fuel and delay costs in the non-time segmented ATFM model. Moreover, Hamdan et al. (2019) considered CO_2 emissions as a function of flight duration and its occupancy rate (that is, number of passengers), and Hamdan et al. (2020) modeled emissions in the ATFM as two linear functions.

In the fifth category, Jardine (2005) quantified CO_2 emissions as a function of the traveled distance and discussed the emission impact using radiative forcing (RF), global warming potential and global temperature potential proposed by the Intergovernmental Panel on Climate Change. The RF metric measures the energy balance change of the lower atmosphere by the greenhouse emissions or collection of different gases. The global warming potential metric calculates the cumulative RF of one kilogram of emitted gas to the same mass of a reference gas, typically CO_2. Like the global warming potential metric, the global temperature potential metric calculates the average surface temperature change. Jardine (2005) indicated that the global temperature potential requires extra work and that no accurate global warming potential measure of aviation emissions has yet been calculated. While the Fourth Assessment Report of the Intergovernmental Panel on Climate Change quantified the RF for 2005 based on 2000 operations data, Lee et al. (2009) updated the RF using new operational data to reflect the increase in traffic volume and fuel use. They also provided RF estimates for 2020 and 2050.

On the other hand, the emission impact on society varies from increased sea levels to increased heatwaves. Foley et al. (2013) concluded that the social cost of carbon depends on the policy scenario. Berger et al. (2022) found that passengers are not willing to pay to offset their emissions in order to fly emission neutral after analyzing actual data. Rathore and Jakhar (2021) proposed a differential carbon tax policy that pushes airlines to align their network design with the policymaker design preferences resulting in social and environmental enhancement. Jiang and Yang (2021) found that SAF quota policy outperforms carbon tax policy when having challenging emission targets and that SAF quota may result in better social welfare if SAF price becomes low. Martinez-Valencia et al. (2021) highlighted that the SAF business model could be successful if governments put policies that increase SAF's social, environmental and economic benefits.

To the best of our knowledge, no previous work has analyzed the impact of SAF from the ATFM perspective, and no previous ATFM model has considered fuel cost, emissions, and fuel type. Therefore, we fill the gap between the two categories by formulating a bi-objective mathematical model that analyzes the trade-off between emissions and network delays based on fuel type.

3. Aircraft fuel consumption and CO_2 emissions

In this section, we illustrate how fuel consumption is modeled as a function of aircraft speed and how it is linked to CO_2 emissions based on fuel type.

3.1. Modeling fuel consumption as a function of speed

As aircraft fuel consumption represents the most significant part of airline operational cost, several attempts have been made to understand the relationship between fuel consumption and other exogenous variables. Achieving a good understanding of this matter helps develop strategies to reduce operational costs. Similar to vehicles, the relationship between aircraft speed and fuel consumption (and consequently CO_2 emissions) is nonlinear. At lower ground speeds, the fuel consumption tends to be high (resulting in higher emissions), which decreases as the speed increases and then increases again. This relationship was reported by Clarke et al. (2008) for several aircraft types based on industrial data. Fuel consumption as a function of aircraft speed can be modeled using industrial data from Akgunduz and Kazerooni (2018). The choice of using the data reported in Akgunduz and Kazerooni (2018), Clarke et al. (2008) is due to data availability and modeling needs (that is, suitability for the ATFM model). Note that Baumann and Klingauf (2020) highlight that many fuel consumption models rely on databases that are not publicly accessible or manual information. In addition, studies that focused on comparing different fuel consumption models can be considered as proof of method and not performance because different benchmarks are used. In this work, we propose the following function (Fig. 1):

$$\zeta(v) = a + b \times \left|\frac{1}{v} - \frac{1}{v_1}\right| + c \times \left|\frac{1}{v} - \frac{1}{v_2}\right| + d \times \frac{1}{v}, \tag{1}$$

Table 1
Fitting error in the proposed function and the function in Akgunduz and Kazerooni (2018).

Measure	Akgunduz and Kazerooni (2018)	This work
Mean absolute error (MAE $= \sum_{v\in V} \lvert \frac{\zeta(v)-\zeta_R(v)}{\lVert V\rVert} \rvert$)	2.1	0.71
Root mean squared error (RMSE $= \sqrt{\sum_{v\in V} \frac{(\zeta(v)-\zeta_R(v))^2}{\lVert V\rVert}}$)	2.42	0.89
Sum squared error (SSE $= \sum_{v\in V} \zeta(v)-\zeta_R(v)$)	58.42	7.85
Mean absolute percentage error (MAPE $= 100\times\sum_{v\in V} \lvert \frac{\zeta(v)-\zeta_R(v)}{\zeta_R(v)} \rvert$)	11.22%	3.99%

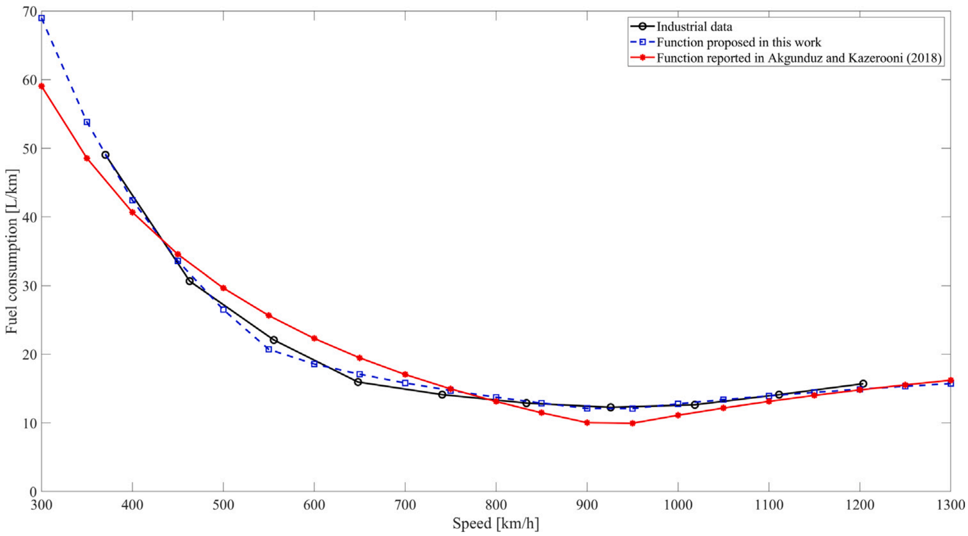


Fig. 1. Speed and fuel consumption relationship based on real data.

where $\zeta(v)$ is the fuel consumption per unit distance as a function of aircraft speed v (L/km), v_1 and v_2 are two speed values selected to facilitate smoothing of the fitting. We tested several values for v_1 and v_2. The values that corresponded to the best fit were $v_1 = \arg\min_v 1.8\times\zeta = 555$ km/h and $v_2 = \arg\min_v \zeta = 926$ km/h. Variables a, b, c, and d are regression coefficients.

To determine the regression coefficients of Eq. (1), a simple optimization model that minimizes the sum of squared errors between the fitted and industrial data is used, and it is given as follows:

$$\min E = \sum_{v\in V} (\zeta(v) - \zeta_R(v))^2, \tag{2}$$

where E is the sum of squared errors between the fitted data and the industrial data in Akgunduz and Kazerooni (2018) and $\zeta_R(v)$ is the industrial fuel consumption data. The optimization of the regression parameters (a, b, c, and d) leads to $a = -5.85km/L$, $b = 10118.60L/h$, $c = 12196.93L/h$, and $d = 9554.03L/h$. Eq. (1) and the optimal parameters result in a very close fit to the real industrial data with $R^2 = 99.43\%$ compared with $R^2 = 95.26\%$ for the fitting reported by Akgunduz and Kazerooni (2018) using a simpler equation, as shown in Fig. 1. Table 1 compares the proposed fitting function and the fitting function of Akgunduz and Kazerooni (2018) under other performance indicators. Note that this is mainly due to the use of two fixed points (v_1 and v_2) in Eq. (1) rather than one, as in Akgunduz and Kazerooni (2018). Finally, the fuel consumption is obtained in liters by multiplying Eq. (1) by distance, which results in the following equation:

$$\xi(R,D) = a\times D + b\times\left|R-\frac{D}{v_1}\right| + c\times\left|R-\frac{D}{v_2}\right| + d\times R, \tag{3}$$

where $\xi(R,D)$ is the total fuel consumed on the trip, D is the distance in km, and R is the time spent in hours.

Remark 1. Eq. (1) has two nonlinear aspects: the speed ($\frac{1}{v}$) and the absolute function ($|.|$). Using the fuel consumption versus the time relationship in Eq. (3) removes the nonlinearity caused by the speed ($\frac{1}{v}$). In Section 4, we show how the nonlinearity caused by the absolute function is resolved.

3.2. Relationship between fuel consumption and CO_2 emissions

We rely on the CORSIA lifecycle CO_2 equivalent (CO_{2eq}) for SAF emission values. These values include the emissions of CO_2, methane and nitrous oxide from well-to-pump activities and CO_2 emissions from well-to-wake fuel combustion (International Civil

Table 2
LCA emissions and fuel price for the used SAFs.

Label	Process	Feedstock	LCA CO_{2eq} emissions (kg CO2e/L)	Minimum fuel selling price (€/L)
SAF-A	FT	Agricultural residues	0.26	1.74
SAF-B		Forestry residues	0.28	0.81
SAF-C[b]		Forestry residues	0.28	1.58
SAF-D		Short rotation woody crops	0.41	0.70
SAF-E		Herbaceous lignocellulosic energy crops	0.35	1.89
SAF-F		Municipal solid waste (0% NBC[a])	0.17	1.35
SAF-G		Municipal solid waste (10% NBC)	0.75	1.35
SAF-H		Municipal solid waste (30% NBC)	1.89	1.35
SAF-I	HFEA	Used cooking oil	0.46	1.16
SAF-J		Palm fatty acid distillate	0.69	0.94
SAF-K		Soybean oil	1.35	0.95
SAF-L		Camelina	1.44	0.99
SAF-M		Palm oil - closed pond (with methane)	1.25	0.99
SAF-N		Palm oil - open pond (without methane)	2.00	0.99
SAF-O	Synthesized ISO-Paraffins	Sugarcane	1.10	1.64
SAF-P	Alcohol-to-Jet	Sugarcane iso-butanol	0.80	1.64
SAF-Q		Forestry residues	0.79	1.83
SAF-R		Corn grain iso-butanol	1.86	1.64

[a]NBC: non-biogenic content.
[b]Similar to SAF-B but with a different price.
All values are calculated using data collected from Yang et al. (2019), International Civil Aviation Organization (2019b), Zhang et al. (2020), Capaz et al. (2021), Martinez-Valencia et al. (2021).

Aviation Organization, 2019b). Note that SAF reduces sulfur emissions significantly and the reduction may reach 100% (Jiang and Yang, 2021; Kousoulidou and Lonza, 2016). The CORSIA lifecycle CO_{2eq} emission is reported in grams of CO_{2eq} per mega joule (g CO_{2eq}/MJ). LCA emissions in g/MJ are converted to kilograms/MJ (kg/MJ) and then multiplied by the specific energy (MJ/kg) and the fuel density (kg/L) to get the emission value in kg/L. The LCA CO_{2eq} emissions of the used SAFs in this work are given in Table 2. The LCA CO_2 emissions resulting from using one liter of CAF (E^{CAF}) used in this work is 3.745 kg/L (De Jong et al., 2017; Yilmaz and Atmanli, 2017).

The projected minimum SAF prices are obtained from Martinez-Valencia et al. (2021), Capaz et al. (2021) and are presented in Table 2. Furthermore, the projected 2035 CAF price is C^{CAF}= €1.35 /L if it follows the oil price (Hayward et al., 2015).

4. Integrating fuel and emissions in the ATFM model formulation

We present a network optimization model for managing flights considering airports' capacities, en-route sector capacities, ground and air delays, path selection, fuel cost, and LCA CO_{2eq} emissions for a one-day planning horizon. The proposed ATFM model considers sets of flights, a set of airports, and a set of en-route airspace sectors. These flights traverse several airspace sectors in predefined paths to reach their destinations. A set of decisions can be executed to manage the flights with regard to the available airports' and sectors' capacities. Ground delay is a decision that implies a postponement of a flight's departure. Air delay results from speed adjustment, which leads to an aircraft spending more time than scheduled in some sectors. Note that allowing the ATFM model to adjust the airplane speed in each sector is a common modeling practice (Bertsimas and Patterson, 1998; Bertsimas and Gupta, 2015). Another decision is to re-route flights to avoid some sectors in the planned path. In some cases, when long delays are assigned to a flight, the airline may decide to cancel the flight. Brueckner and Zhang (2010) reported that fuel cost affects the airline network design choice and that this is a strategic decision. The proposed ATFM model takes the strategic airline decisions as input by considering flight scheduled paths defined by airlines and sets of alternative paths for re-rerouting. In addition, the model considers continuing flights, where an aircraft can perform more than one trip after a specified turnaround period.

The model considers en-route flights, which leads to the definition of several flight types, as presented in Table 3. In addition, a flight that has part of its path outside the network, that is, a sector not within the studied network, is represented as a pair of two flights and is referred to as Type E. The first flight in the pair represents the first leg of the flight from the first sector to the last sector before it exits the network. The second flight represents the second leg of the flight from its first sector after it enters the network until it lands or leaves the network. Type E flights are treated in a similar manner to continuing flights. Each leg of a type E flight can belong to type B, C, or D.

The airspace is divided into elementary sectors, which are essential airspace elements that cannot be split into smaller units. During the day, two or more elementary sectors can be merged to form a large collapse sector and reduce the number of air traffic controllers needed. Splitting a collapse sector into its elementary sectors results in larger airspace capacity. In this work, we considered the dynamic nature of the elementary and collapse sectors while modeling the network. Information about the airspace sector's opening scheme can be obtained from the EUROCONTROL demand data repository (DDR2). It is worth noting that the flight

Table 3
Different types of flights in the region-based ATFM based on airport location and departure/arrival times.

Flight type	Departure airport/time	Arrival airport/time
Type A	The airport is inside the network and the take-off occurs during the planning horizon	The airport is inside the network and the landing occurs during the planning horizon
Type B	The airport is outside the network or the take-off occurs before the start of the planning horizon	The airport is inside the network and the landing occurs during the planning horizon
Type C	The airport is inside the network and the take-off occurs during the planning horizon	The airport is outside the network or the landing occurs after the end of the planning horizon
Type D	The airport is outside the network or the take-off occurs before the start of the planning horizon	The airport is outside the area or the landing occurs after the end of the planning horizon

path in DDR2 can be obtained as a set of elementary sectors. In this work, unless otherwise specified, the word "sector" will be used to refer to either an elementary or a collapse sector, as given in the opening scheme schedule.

It is hypothesized that the integration of fuel cost and emissions in the ATFM network will reduce air delays to minimize fuel consumption.

4.1. Environmental objective

The total CO_{2eq} emitted (Eq. (4)) is calculated by multiplying the total traveling time (based on selected paths and speeds) by a suitable emission factor based on the fuel type used. The first part of Eq. (4) is multiplied by $w^{f,z}_{j,\underline{T}^{f,z}_j}$ to ensure that it equals zero if a flight does not enter the elementary sector by $t = \underline{T}^{f,z}_j$.

$$\min E = E^{CAF} \times \sum_{f\in\mathcal{F}} \sum_{z\in\mathcal{Z}_f} \sum_{j\in\mathcal{P}^z_f} \left(aD^{f,z}_j w^{f,z}_{j,\underline{T}^{f,z}_j} + b\left|\psi R^{f,z}_j - \frac{D^{f,z}_j}{v_1} w^{f,z}_{j,\underline{T}^{f,z}_j}\right| \right. \\ \left. +c\left|\psi R^{f,z}_j - \frac{D^{f,z}_j}{v_2} w^{f,z}_{j,\underline{T}^{f,z}_j}\right| + d\psi R^{f,z}_j \right). \tag{4}$$

Remark 2. The fuel consumption equation for calculating emissions (Eq. (4)) is nonlinear because of the absolute functions. Since it is a minimization problem, the absolute function can be transformed into a linear function by introducing a new decision variable and two constraints for each absolute function as follows:

- $Y1^{f,z}_j$ and $Y2^{f,z}_j$: continuous decision variables used to represent the linear transformation of the absolute functions $\left|\psi R^{f,z}_j - \frac{D^{f,z}_j}{v_1} w^{f,z}_{j,\underline{T}^{f,z}_j}\right|$ and $\left|\psi R^{f,z}_j - \frac{D^{f,z}_j}{v_2} w^{f,z}_{j,\underline{T}^{f,z}_j}\right|$, respectively.

Eq. (4) is then replaced by:

$$\min E = E^{CAF} \times \sum_{f\in\mathcal{F}} \sum_{z\in\mathcal{Z}_f} \sum_{j\in\mathcal{P}^z_f} aD^{f,z}_j w^{f,z}_{j,\underline{T}^{f,z}_j} + bY1^{f,z}_j + cY2^{f,z}_j + d\psi R^{f,z}_j, \tag{5}$$

with the following constraints:

$$R^{f,z}_j - \frac{D^{f,z}_j}{v_1} w^{f,z}_{j,\underline{T}^{f,z}_j} \le Y1^{f,z}_j, \qquad f\in\mathcal{F}, z\in\mathcal{Z}_f, j\in\mathcal{P}^z_f, \tag{6}$$

$$\frac{D^{f,z}_j}{v_1} w^{f,z}_{j,\underline{T}^{f,z}_j} - R^{f,z}_j \le Y1^{f,z}_j, \qquad f\in\mathcal{F}, z\in\mathcal{Z}_f, j\in\mathcal{P}^z_f, \tag{7}$$

$$R^{f,z}_j - \frac{D^{f,z}_j}{v_2} w^{f,z}_{j,\underline{T}^{f,z}_j} \le Y2^{f,z}_j, \qquad f\in\mathcal{F}, z\in\mathcal{Z}_f, j\in\mathcal{P}^z_f, \tag{8}$$

$$\frac{D^{f,z}_j}{v_2} w^{f,z}_{j,\underline{T}^{f,z}_j} - R^{f,z}_j \le Y2^{f,z}_j, \qquad f\in\mathcal{F}, z\in\mathcal{Z}_f, j\in\mathcal{P}^z_f. \tag{9}$$

Constraints (6)–(7) replace the absolute function of v_1, that is, they ensure that the variable $Y1^{f,z}_j$ obtains the maximum value of $R^{f,z}_j - \frac{D^{f,z}_j}{v_1} w^{f,z}_{j,\underline{T}^{f,z}_j}$ and $\frac{D^{f,z}_j}{v_1} w^{f,z}_{j,\underline{T}^{f,z}_j} - R^{f,z}_j$. Similarly, constraints (8)–(9) replace the absolute function of v_2.

It is worth mentioning that constraint (10) is required to calculate the total time in hours spent in elementary sector j by flight f using route z.

$$R_j^{f,z} = \psi \times \left(\sum_{t \in T_j^{f,z}} w_{j,t}^{f,z} - \sum_{t \in T_{j'}^{f,z}} w_{j',t}^{f,z} \right),$$
$$f \in \mathcal{F}, z \in \mathcal{Z}_f, j \in \mathcal{P}_f^z : j' = \mathcal{P}_f^z(j+1), \tag{10}$$

4.2. Economic objective

The ATFM network cost (Eq. (11)) consists of the total ground and air delays for type A and C flights (Eqs. (11a) and (11b), respectively), total air delays for type B and D flights (Eq. (11c)), total cancelation penalty (Eq. (11d)), and total penalty for selecting a route other than the scheduled route (Eq. (11e)).

$$\min \; C = C_1 + C_2 + C_3 + C_4 + C_5, \tag{11}$$

$$C_1 = \sum_{\substack{f \in \mathcal{F}^A \cup \mathcal{F}^C \\ j = \mathcal{P}_f^z(1)}} \sum_{z \in \mathcal{Z}_f} \sum_{t \in T_j^{f,z} : t \geq d_f + l_{origin_f}^f} C_{ground}^f \left(t - d_f - l_{origin_f}^f \right)^{1+\varphi} \left(w_{j,t}^{f,z} - w_{j,t-1}^{f,z} \right), \tag{11a}$$

$$C_2 = \sum_{f \in \mathcal{F}^A \cup \mathcal{F}^C} \sum_{z \in \mathcal{Z}_f} \max \Bigg\{ 0, \sum_{k \in \{dest_f, vdest\}} \sum_{t \in T_k^{f,z} : t \geq a_f^{k,z^s}} C_{air}^f \left(t - a_f^{k,z^s} \right)^{1+\varphi} \left(w_{k,t}^{f,z} - w_{k,t-1}^{f,z} \right) - \sum_{t \in T_j^{f,z} : t \geq d_f + l_{origin_f}^f} C_{ground}^f \left(t - d_f - l_{origin_f}^f \right)^{1+\varphi} \left(w_{j,t}^{f,z} - w_{j,t-1}^{f,z} \right) \Bigg\}, \tag{11b}$$

$$C_3 = \sum_{f \in \mathcal{F}^B \cup \mathcal{F}^D} \sum_{k \in \{dest_f, vdest\}} \sum_{z \in \mathcal{Z}_f} \sum_{t \in T_k^{f,z} : t \geq a_f^{k,z^s}} C_{air}^f \left(t - a_f^{k,z^s} \right)^{1+\varphi} \left(w_{k,t}^{f,z} - w_{k,t-1}^{f,z} \right), \tag{11c}$$

$$C_4 = \sum_{f \in \mathcal{F}^A \cup \mathcal{F}^C} C_{cancel}^f \left(1 - \sum_{\substack{z \in \mathcal{Z}_f, \\ k = origin_f}} w_{k, \underline{T}_k^{f,z}}^{f,z} \right) + \sum_{f \in \mathcal{F}^B \cup \mathcal{F}^D} C_{cancel}^f \left(1 - \sum_{\substack{z \in \mathcal{Z}_f, \\ j = \mathcal{P}_f^z(1)}} w_{j, \underline{T}_j^{f,z}}^{f,z} \right), \tag{11d}$$

$$C_5 = \sum_{f \in \mathcal{F}} \sum_{z \in \mathcal{Z}_f \setminus \{z^s\}} \sum_{k \in \{dest_f, vdest\}} C_{reroute}^{f,z} w_{k, \underline{T}_k^{f,z}}^{f,z}, \tag{11e}$$

In Eq. (11b), the first part calculates the delay in arrivals, whereas the second part removes from it ground delay so that the final value represents air delay. In addition, the maximum function sets air delay to zero in the case of early arrivals, as an aircraft may be able to arrive on time or earlier by speeding up to compensate for ground delays. This maximum function is converted to a linear function by introducing a new decision variable ($Y^{f,z}$) and two constraints, as follows:

$$C_2 = \sum_{f \in \mathcal{F}^A \cup \mathcal{F}^C} \sum_{z \in \mathcal{Z}_f} Y^{f,z}, \tag{11 b}$$

$$\sum_{k \in \{dest_f, vdest\}} \sum_{t \in T_k^{f,z} : t \geq a_f^{k,z^s}} C_{air}^f \left(t - a_f^{k,z^s} \right)^{1+\varphi} \left(w_{k,t}^{f,z} - w_{k,t-1}^{f,z} \right) - \sum_{t \in T_k^{f,z} : t \geq d_f, k = origin_f} C_{air}^f \left(t - d_f \right)^{1+\varphi} \left(w_{k,t}^{f,z} - w_{k,t-1}^{f,z} \right) \leq Y^{f,z}, \quad f \in \mathcal{F}^A \cup \mathcal{F}^C \; z \in \mathcal{Z}_f, \tag{12}$$

$$Y^{f,z} \geq 0, \quad f \in \mathcal{F}^A \cup \mathcal{F}^C \; z \in \mathcal{Z}_f, \tag{13}$$

Note that:

- The objective function (Eq. (11)) can be changed to minimize the total cost, which includes the total fuel cost, by adding a sixth term (C_6). This sixth term results from replacing the emission parameter E^{CAF} by the fuel cost parameter C^{CAF} in the emission given by Eq. (4).
- The effect of SAF on network decisions can be tested by replacing E^{CAF} in Eq. (4) by E^{SAF}. In addition, when the fuel cost is considered (as explained in the previous remark), the fuel cost parameter C^{CAF} is changed to C^{SAF}.

4.3. ATFM network characteristic

ATFM network modeling involves considering several constraints for the departure and arrival airport capacities, airspace sector capacities, flight paths and continuing flight connectivity, re-routing, and time connectivity. These constraints are described in detail in the Supplementary Material (see Equations (A.1)–(A.17)).

5. Solution approach

The proposed model deals with conflicting objectives (CO_{2eq} emissions and network costs). Different techniques can be used to help decision-makers analyze the trade-off between these objectives, such as the weighted sum method, lexicographic method, weighted min–max method, goal programming and ϵ-constraint method (Marler and Arora, 2004). Among the different techniques, we adopted the weighted comprehensive criterion method (WCCM), which is based on minimizing the total variation of each objective function from its optimal value. This method normalizes each objective function to remove its magnitude effect on the final solution and to become dimensionless. Note that decision-maker preference can be incorporated easily when using the WCCM by modifying the weight values. It has been successfully applied in many fields, such as supply chain management (Hamdan et al., 2018) and product design optimization (Cheaitou et al., 2019).

To apply the WCCM, each objective function i ($i = 1, \dots, O$) is first solved separately, subject to all constraints, in order to obtain its optimal value (f_i^{opt}). Each objective function i is then transformed into its normalized version according to the rule given by Eq. (14).

$$f_i^T = \begin{cases} \frac{f_i - f_i^{opt}}{f_i^{opt}} & \text{if } f_i \text{ is to be minimized} \\ \frac{f_i^{opt} - f_i}{f_i^{opt}} & \text{if } f_i \text{ is to be maximized.} \end{cases} \tag{14}$$

Subsequently, each transformed objective function is multiplied by an importance weight (β_i) and, finally, the weighted transformed objectives are summed up using Eq. (15), resulting in a single objective function that represents the total variation of all the objective functions. This single objective is minimized to solve the multi-objective function problem. Note that $\sum_{i=1}^{O} \beta_i = 1$.

$$Z = \sum_{i=1}^{O} \beta_i \times f_i^T. \tag{15}$$

Using the WCCM and varying the importance weights (β_i, $i = 1, \dots, O$), different Pareto optimal solutions (which are non-dominated solutions) can be obtained to study the trade-off between several objectives.

To provide decision-makers with a reasonable number of solutions, a clustering technique is used to group the Pareto solutions into three clusters. Afterward, one solution from each cluster (for example, the closest solution to the centroid of the cluster) can be chosen as a representative solution for the cluster. In this work, the k-means approach, which aims to minimize the variance within each cluster, was used to split the Pareto solutions into three clusters. The first cluster represents emission-focused solutions, which contain several solutions with lower emission values, but their network costs may be high. The second cluster contains balanced solutions between network costs and emissions. The last cluster represents network-focused solutions that contain Pareto solutions with lower network costs and higher emissions.

6. Managerial insights from the Swedish airspace

In this section, we use the model to analyze the effects of emissions and fuel types on the network performance. We use the DDR2 to obtain the required flight data. DDR2 is a database established by the EUROCONTROL, which provides historical flight and airspace information such as flight trajectories, airspace configurations, and opening times. We focused on the Swedish airspace, and analyzed the data spanning July 27–29, 2018. Table 4 summarizes the details of each instance. Each period t accounted for 15 min. The maximum allowable delay for each flight was set as two hours. The ground and air delay parameters were obtained from Eurocontrol (2018) as follows: C_{air}^{f} = €2190 per time period, C_{ground}^{f} = €1350 per time period, and C_{cancel}^{f} = €96695 per flight. The re-routing cost was assumed to be $C_{reroute}^{f,z}$ = €700 per flight. Note that the air delay cost includes the cost of extra fuel consumed during the additional flying time, and this cost is between 7% and 50% of the air delay cost. The fuel cost component of the air delay cost depends on the delay duration and aircraft type (Performance Review Unit, 2004). In this work, we reduced the air delay cost stated in Eurocontrol (2018) by 20% to eliminate fuel cost redundancy. Each day of the operation was optimized under four different cases as follows:

1. Case 1: Minimizing the network costs (the model defined by Eq. (11) and constraints (12) and (13) in Section 4.2, and the network constraints (A.1–(A.17) in the Supplementary Material).
2. Case 2: Minimizing both the total CO_{2eq} emitted and the network costs (the model defined by Eqs. (5) and (11) subject to constraints (A.1)–(A.17) in addition to the same constraints of Case 1 under equal importance weights ($\beta_1 = \beta_2 = 50\%$)).
3. Case 3: Minimizing the total costs, including the fuel and network costs (similar to Case 1 but considering the sixth cost element as described in Section 4.1).
4. Case 4: Minimizing the total costs and CO_{2eq} emitted under equal importance weights.

In Cases 2–4, the problem was solved for both CAF and SAF. The model was implemented using Julia Programming Language 1.6.2 (Bezanson et al., 2017). The branch-and-cut algorithm in CPLEX 20.1.0 was used to solve the optimization model. The analysis was carried out using a laptop equipped with an Intel(R) Core(TM) i7-9750H CPU @ 2.6 GHz and 16 Gb of RAM, and running Windows 10 Home 64-bit operating system. Each instance was solved to optimality in less than 3 min.

Table 4
Details of the airspace structure and flights types.

	July, 2018		
Day	27	28	29
Total type A flights	141	84	187
Total type B flights	144	305	350
Total type C flights	141	315	350
Total type D flights	410	986	1027
Total type E flights	1	1	1
No of airports[a]	25	23	26
No of elementary sectors	29	29	29
No of sectors in the opening scheme	41	30	38

[a]The last airport is the virtual airport ($vdest$).

Remark 3. Note that the proposed model can be modified to define one cruising speed for each flight instead of a cruising speed for each flight and each sector. We compare the two situations: optimizing one cruising speed for each flight and allowing the speed to vary in each sector. We use the fuel consumption as an indicator to reflect the speed change. The relative difference between the two situations were found to be 0.37, 0.18 and 0.35% for July 27–29, 2018, respectively. This can be attributed to the constraint that limits the minimum and the maximum times in each sector for each flight to keep the speed bounded between the minimum allowable and the maximum allowable.

6.1. Impact of fuel cost on the ATFM network

We studied the impact of considering fuel cost on network costs and decisions (SRQ #1). The majority of ATFM models in the literature considered only network costs, such as penalties on cancelation, re-routing, ground delays, and air delays. Some of them used aircraft speed to manage delays. Although this helps to reduce delays, it increases fuel consumption and, consequently, emissions. Fig. 2 illustrates changes in the ATFM network costs and amount of fuel consumed based on the objective function type in a single objective formulation, and Fig. 3 shows the changes in the total ground delay, total air delay, and total re-routing. Changes are calculated with respect to Case 1 as follows $100 \times \frac{X - X_{Case\ 1}}{X_{Case\ 1}}$, where a negative change indicates a reduction.

In Case 1, the model considers minimizing the network costs and does not consider fuel costs. This resulted in minimal network disturbances.

When CAF cost was included (Case 3), the network costs increased by 27.43%, 32.12%, and 27.76% on July 27–29, 2018, respectively, compared to Case 1. The increase in network costs comes at a fuel cost saving of approximately 4.72% each day. This indicates that reducing the network cost by 1% leads to an increase in the amount of fuel consumed by 0.16%. Our analysis showed the impact of considering fuel cost on air delays, in which airplanes in some situations slow down to fly near their optimal speeds and reduce fuel consumption, thereby resulting in more air delays (Fig. 3(b), July 28, 2018). For July 27 and 29, 2018, flying near the optimal speed reduced air delays but increased ground delays and path re-routings (Figs. 3(a) and 3(c)). Thus, considering fuel results in more ground delays and re-routings while the effect on air delays depends also on the network conditions, such as configurations, number of flights, available alternative paths.

To understand the effect of SAF on the network, we repeated the analysis using C^{SAF} and sustainable fuel types. On average, the SAF achieved slight fuel savings ranging between 0.01% and 0.07% compared to CAF; however, it had slightly increased network costs between 0.24% and 1.55% compared to CAF. This is mainly due to the high expected prices of SAF compared to CAF. Meanwhile, the CAF cost in the cost objective function significantly increased re-routing decisions (almost four times) compared to when fuel was not considered, especially when the new routes had the same length as the scheduled route and were less congested. It also increased the ground delays by an average of 31%. Air delays were the least impacted decisions (varying between −2% and 6%). The slight increase (reduction in some cases) in air delays is because the model avoids increasing the flying time to reduce fuel consumption. Moving from CAF to SAF increased the re-routing on average by 4.47%, and decreased the ground delays and air delays by 0.24% and 0.4%, respectively when SAF price is higher than CAF. On the other hand, when SAF prices are lower than CAF, ground delays, air delays and re-routing are reduced by 15.5%, 9.6% and 6.96%, respectively (Fig. 3).

6.2. LCA CO_{2eq} emission and network cost trade-off

The trade-off between the network costs (delay and re-routing costs) and emissions was analyzed through the Pareto frontier (SRQ #2). Figs. 4–6 illustrate the changes in the network costs and CO_{2eq} emitted for July 27–29 using CAF and SAF with and without fuel cost consideration (Cases 2 and 4). These Pareto frontiers were generated by varying β_1 from 0 to 1 in increments of 0.02. The trade-off between network costs and LCA CO_{2eq} emissions is given in Table 5 for both CAF and SAF for Cases 2 and 4.

When fuel cost was not considered in the model, a decrease of 1% in the network costs increased the emissions by an average of 0.18% when CAF was used and 0.17% SAF was used. For each 1% decrease in network costs when considering fuel consumption, the increase in emissions was, on average, 7.43% when CAF was used and between 7.59% and 29.7% when SAF was used depending on the SAF type (Table 5). SAF-A, B, E, F, G, H and Q has the lowest trade-off value and SAF-J, K, L, M, and N has the highest values

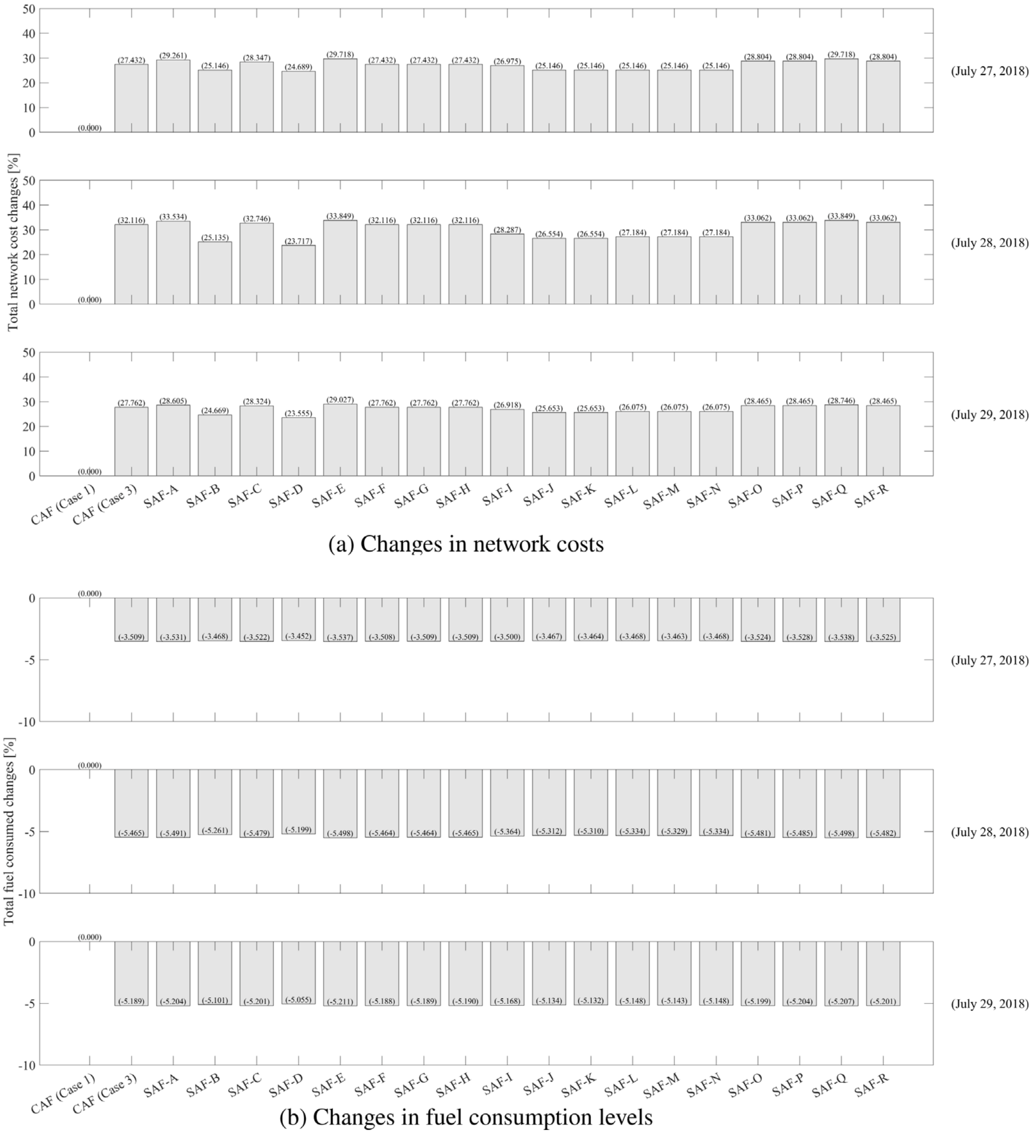


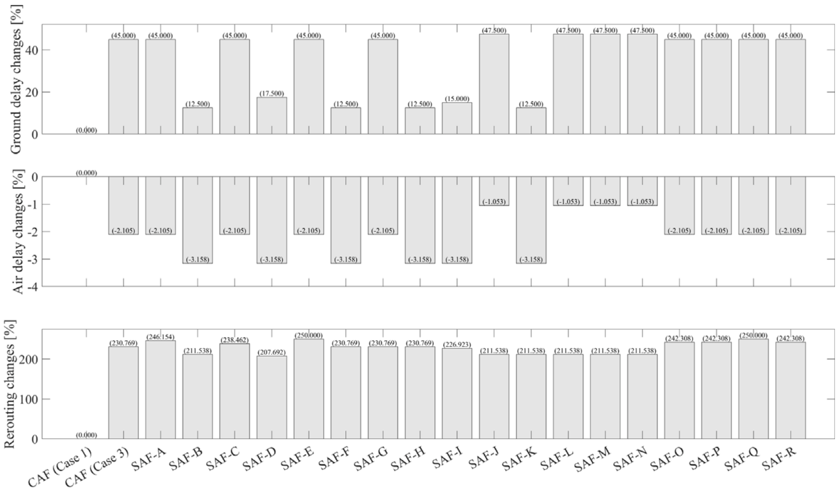
Fig. 2. Changes in network costs and fuel consumption with respect to CAF (Case 1).

among other SAFs. These trade-off values have a positive weak linear dependency on emission values (coefficient of correlation of 0.45) and a negative weak linear dependency on fuel prices (coefficient of correlation of −0.51). This means that fuel price or emission value alone cannot be used to predict the network trade-off.

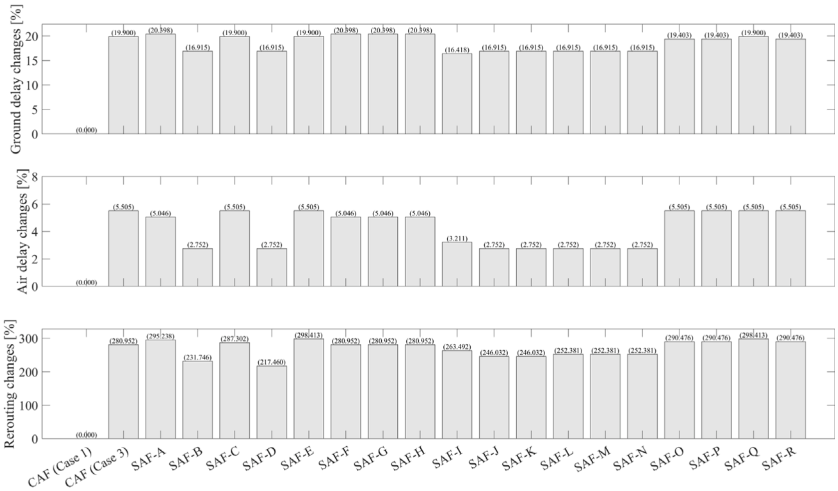
The clustering of all the Pareto solutions of Cases 2 and 4 into the three clusters mentioned earlier shows that the majority of Case 2 solutions (obtained using 0.02 increments) belong to the network-focused cluster. The reason behind the increase in delays when accounting for the fuel cost is because the model tries to set the aircraft speed near its optimal fuel consumption point. Based on the Pareto frontiers, SAF-A, B, C, D, E, F, and I can be grouped together (solid line cluster "-" in Figs. 4–6), SAF-G, J, P, and Q form the second cluster (dashed line cluster "–" in Figs. 4–6), SAF-K, L, M, and O form the third cluster (dotted line ".." cluster) and the last cluster groups SAF-H, N, and R (dash-dotted line cluster "-."). The Pareto frontier cluster does not match with clusters done considering fuel emissions and prices. From the clustering results of both the trade-offs and the Pareto frontiers, one can observe that small CO_{2eq} reductions (i.e. low trade-off) are associated with fuels that result in small to moderate total emissions (the first and second clusters).

6.3. Carbon price under an emission policy

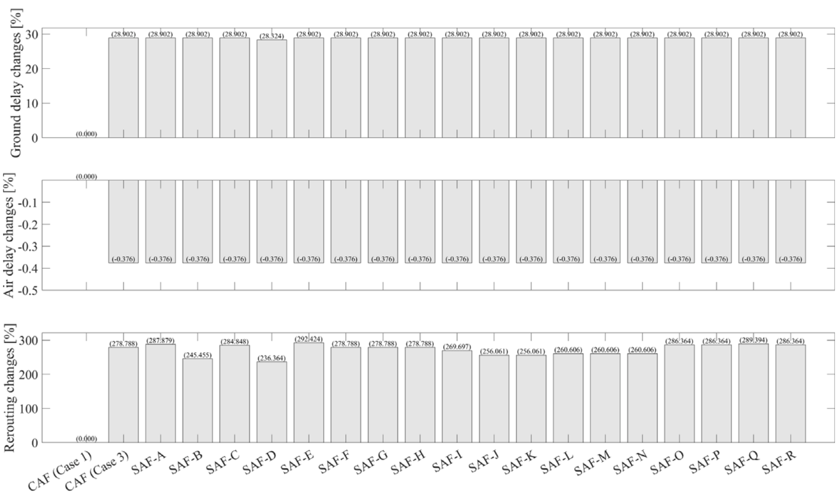
Fig. 7 illustrates how the performance of the network is affected by changing the type of fuel from CAF to SAF under bi-objective considerations. Change percentages are calculated as $100 \times \frac{X - X_{CAF}}{X_{CAF}}$, where a negative change indicates a reduction. Transitioning



(a) July 27, 2018



(b) July 28, 2018



(c) July 29, 2018

Fig. 3. Effect of fuel cost on network decisions (ground delay, air delay and re-routing). Changes are with respect to CAF (Case 1).

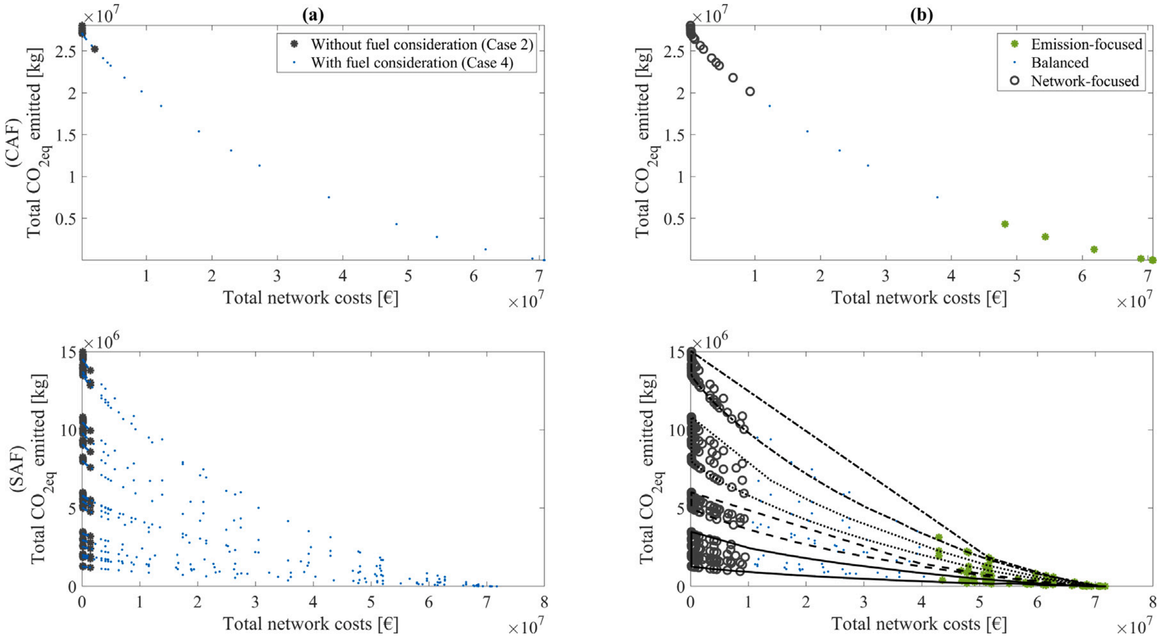


Fig. 4. Pareto solution for day 27 using CAF and SAF: (a) Cases 2 and 4, (b) Clustered Pareto solutions.

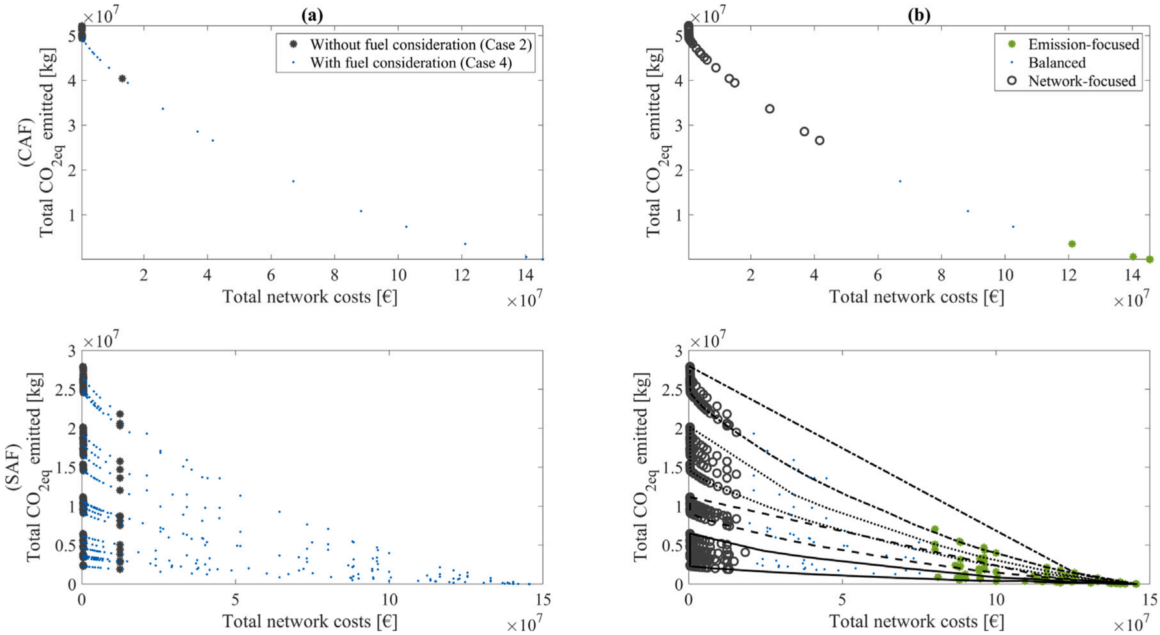


Fig. 5. Pareto solution for day 28 using CAF and SAF: (a) Cases 2 and 4, (b) Clustered Pareto solutions.

from CAF to SAF, in addition to the environmental effect, results in a reduction in fuel consumption between 0.49% and 1.70% for SAFs with higher price than CAF (Fig. 7(c)). This fuel reduction comes at the expense of a significant increase (between 40.91% and 164.25%) in network costs (delay and re-routing costs). The motivation for this fuel reduction is the increased fuel price, where, although the consumed fuel when using SAF is less than that when using CAF, the total fuel cost when using SAF is higher than that when using CAF by an average of 25.2%. For less expensive SAFs compared to CAF, fuel consumption increased by a maximum of 0.06% to reduce network costs by a maximum of 3.29% (Fig. 7(a)). Note that we repeated the analysis over the entire month of July, and we observed the increase in re-routings when transitioning from CAF to SAF. The monthly average increase in re-routing was around 3.5%, and in some days, it could reach up to 7.1% (Fig. 8).

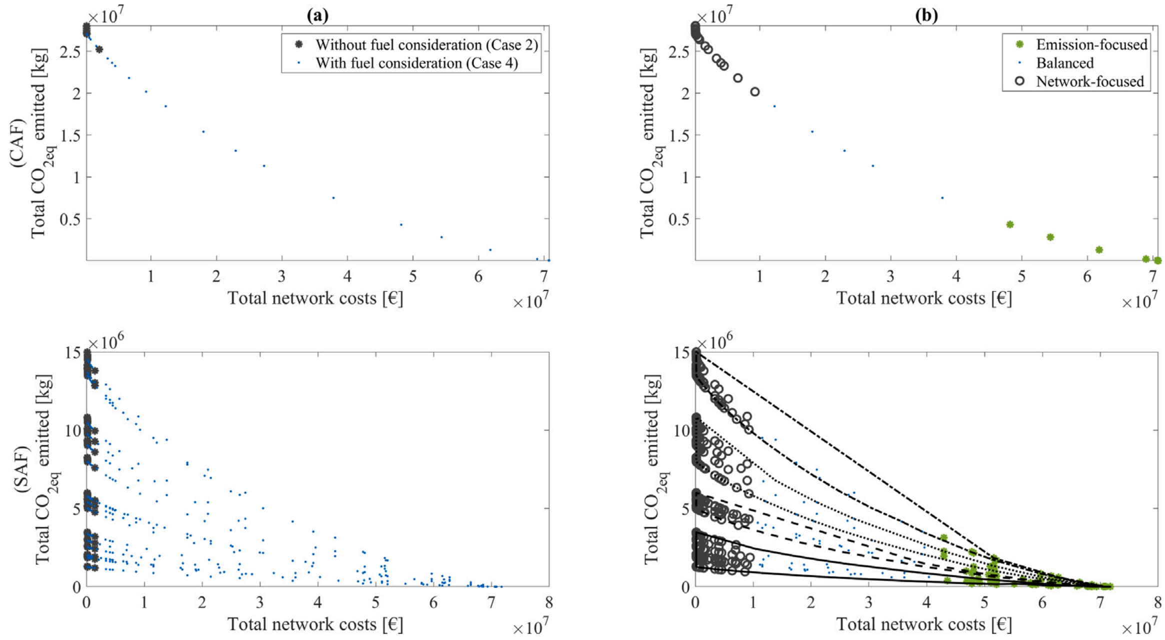


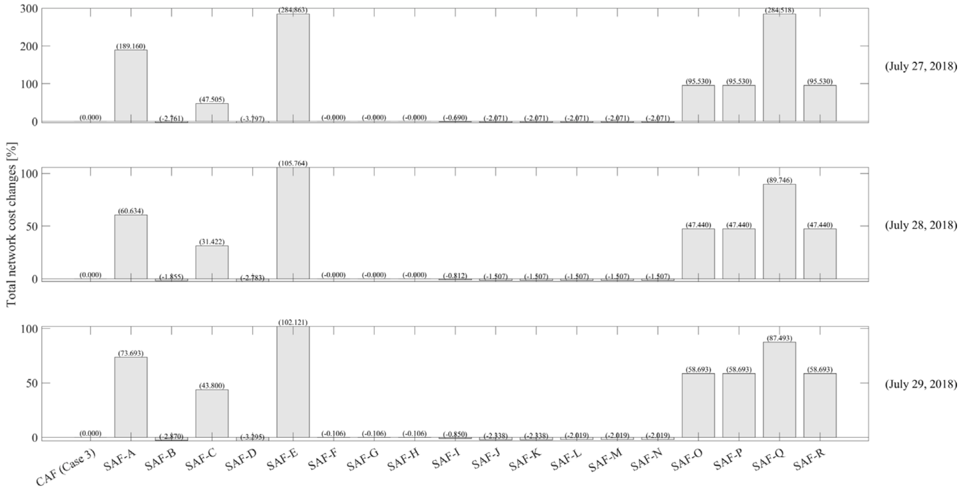
Fig. 6. Pareto solution for day 29 using CAF and SAF: (a) Cases 2 and 4, (b) Clustered Pareto solutions.

Table 5
Percentage increase in LCA CO_{2eq} emissions for each 1% reduction in network costs.

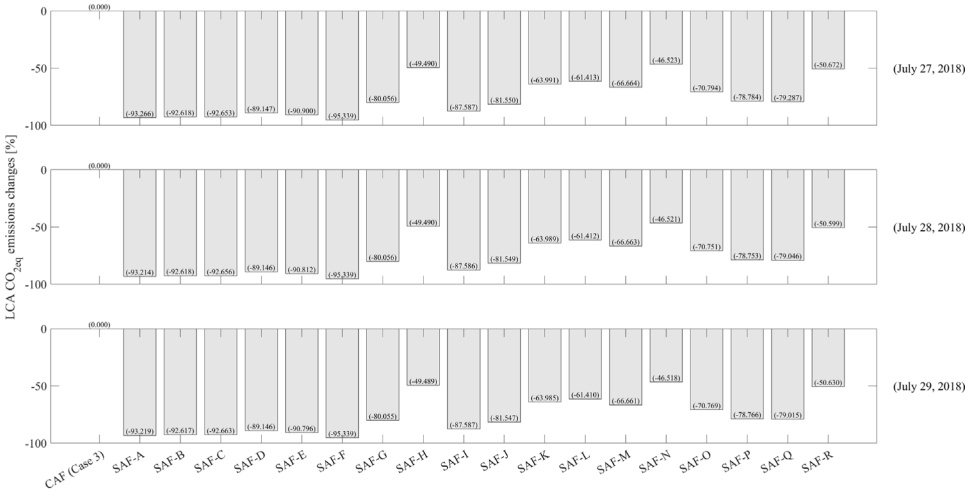
Case	Fuel type	July 27, 2018	July 28, 2018	July 29, 2018
2	CAF	0.097	0.226	0.229
	SAF	0.078	0.217	0.225
4	CAF	4.617	12.359	5.319
	SAF - A	4.261	18.177	5.178
	SAF - B	5.670	10.739	8.031
	SAF - C	6.274	35.685	5.802
	SAF - D	7.148	17.460	12.513
	SAF - E	5.455	14.162	7.288
	SAF - F	5.111	12.316	5.351
	SAF - G	5.111	12.315	5.351
	SAF - H	5.111	12.313	5.351
	SAF - I	6.865	20.728	6.257
	SAF - J	12.369	63.932	12.823
	SAF - K	12.500	61.931	12.527
	SAF - L	17.217	54.035	10.593
	SAF - M	17.212	54.031	10.591
	SAF - N	17.217	54.036	10.593
	SAF - O	5.756	29.686	5.308
	SAF - P	5.758	29.692	5.310
	SAF - Q	5.877	15.709	6.849
	SAF - R	5.756	29.688	5.308

To understand the viability of SAF (SRQ #3), we calculated the required carbon price under an emission policy to compensate for the cost increase from the emission savings. We focused on SAF with higher price than CAF as cheaper SAFs needs no compensation when switching from CAF to SAF. For the three days, the average emissions saving, calculated as “the total emission using CAF – the total emission using SAF”, is shown in Fig. 9(a). Meanwhile, the average total increase in fuel and network costs, calculated from the optimal solution when using CAF and SAF as “total cost using SAF – the total cost using CAF”. This cost difference comes from the average increase in the fuel cost (when moving from CAF to SAF) and the average increase in the network costs as shown in Fig. 9(b) and (c). This means that the carbon price per ton of LCA CO_{2eq} needed to neutralize the increased cost of SAF resulting from emissions saving can be calculated by dividing the average total increase in fuel and network costs by the average emissions saving as shown in Fig. 9(d).

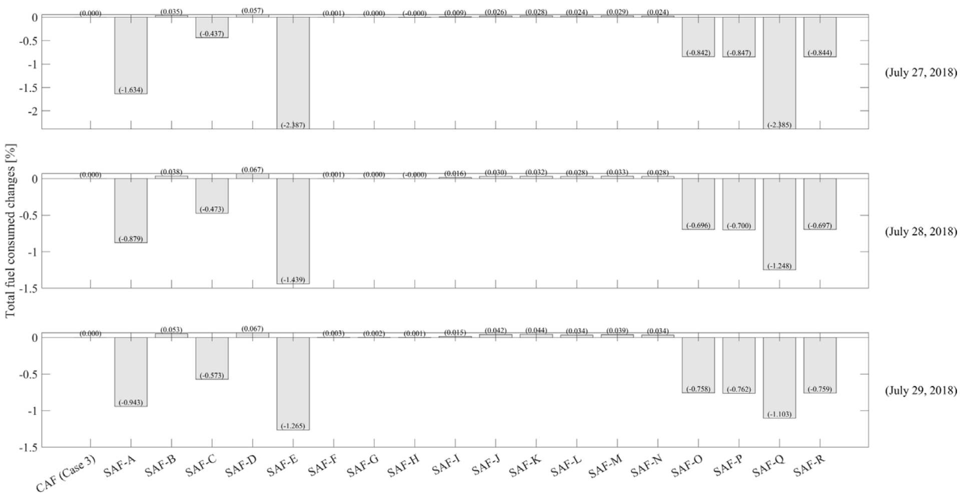
To account for uncertainty in fuel prices, we considered that the CAF price might increase or decrease by 5% and 10% as follows (C^{CAF} [€/L] = {1.215, 1.283, 1.350, 1.418, 1.485}). We also considered a potential drop in SAF prices by −30%, −20% and −10%. In addition, we consider a potential increase by 10, 20, and 30%. We repeated the above analysis for all combinations of the CAF



(a) Changes in the total network cost



(b) Changes in the total emission



(c) Changes in the total fuel consumption

Fig. 7. Effect of switching from CAF to SAF. Changes are calculated with respect to CAF (Case 4).

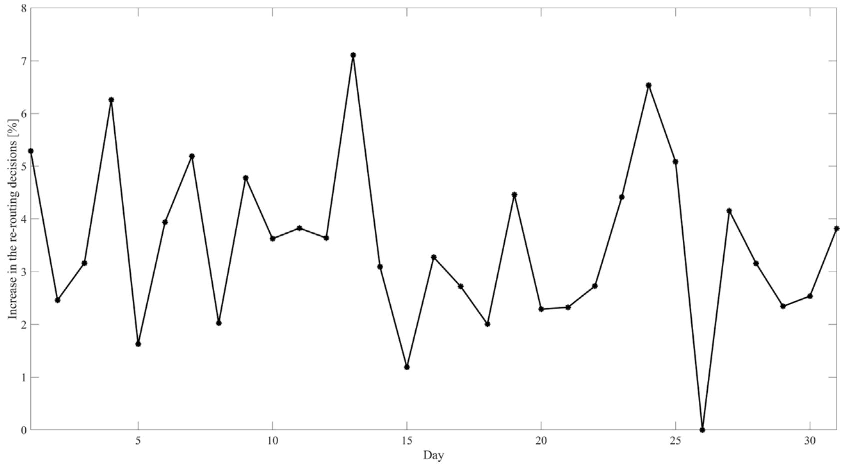


Fig. 8. Increase in re-routing decisions when transitioning from CAF to SAF (average of different SAFs) during the month of July.

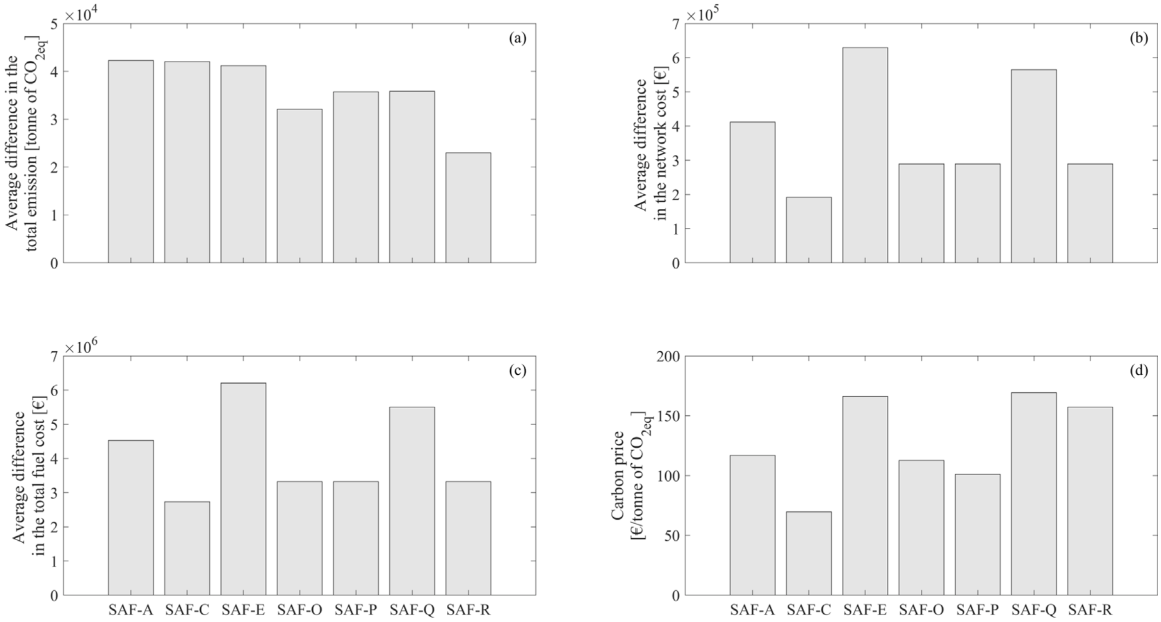
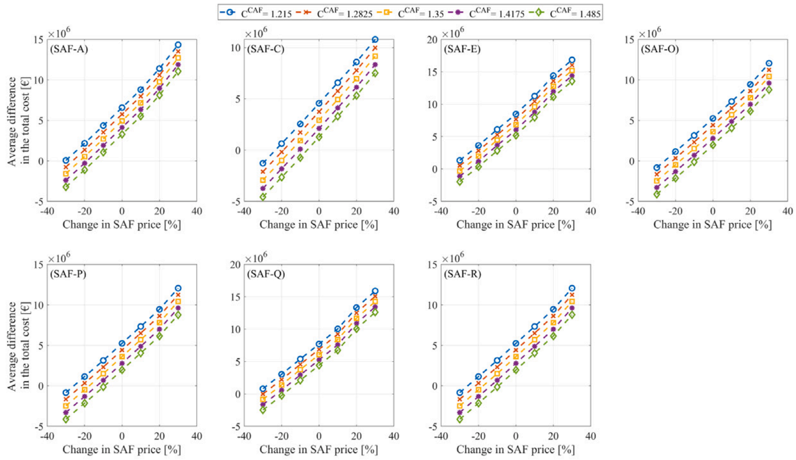


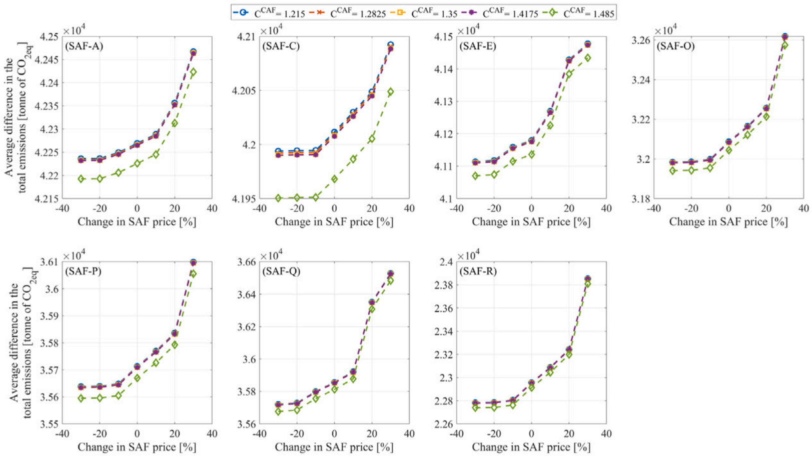
Fig. 9. Average emission savings, network cost increase, fuel cost increase and carbon price needed to balance the switch from CAF to SAF.

and SAF prices. The sensitivity analysis results are shown in Fig. 10. Fig. 10 shows the impact of varying CAF and SAF prices on the total cost difference, total emission difference, and carbon price required to balance the increase in the total cost and emission reduction.

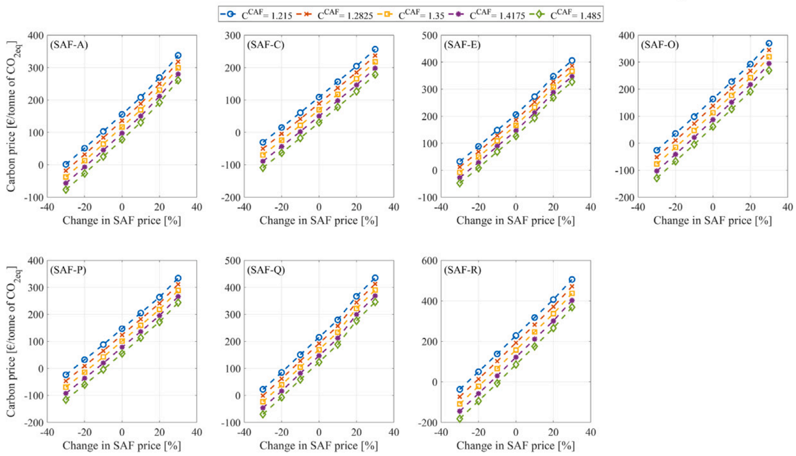
The increase in CAF price reduces the difference in the total cost between CAF and SAF by an average of €8.2129×10^5 for each 5% increase in the price of CAF, which is 19.78% of the total cost difference at C^{CAF}=€1.35/L and the original C^{SAF} for each type (Fig. 10(a)). Decreasing the SAF price by €0.01/L reduces the difference in the total cost between SAF and CAF by €1.3312×10^5, which is 3.18% of the total cost difference at C^{CAF}=€1.35/L and the original C^{SAF} for each type. The linear relationship between the SAF price and the average total cost difference is due to the dominating effect of the fuel cost part in the bi-objective optimization model. Increasing the SAF price forces flights to fly close to their optimal speeds and consequently results in more emission savings, that is, less CO_{2eq} emissions (Fig. 10(b)). Meanwhile, reducing the CAF price below €1.4175/L does not affect the emissions saving; hence, the difference in the total emissions remains unchanged (coinciding lines in Fig. 10(b)). However, increasing the CAF price to €1.485 /L reduces the emission savings by an average of 0.114% when moving from CAF to SAF. Increasing the CAF price by 5% reduces the carbon price by an average of €23.66/ton of CO_{2eq}. Reducing the SAF price reduces the carbon price at a rate of €3.81/ton of CO_{2eq} for each €0.01 reduction in the SAF price (Fig. 10(c)).



(a) the average difference in the total cost [€]



(b) the average difference in the total emission [ton of CO_{2eq}]



(c) the carbon price needed to compensate for the cost increase from the emission savings [€/tons of CO_{2eq}]

Fig. 10. Impact of varying SAF and CAF prices on costs and emissions.

7. Policy implications

In this section, we first discuss SAF's economic, environmental and social impacts within the ATFM context. We then study the effect of SAF on different emission policies within the ATFM context.

7.1. Economic, environmental and social impacts of SAF within the ATFM context

Fuel types have different impacts from economic, environmental, and social perspectives. From an economic perspective, fuel costs account for approximately 24% of airline expenses. While the current ATFM models modify flight schedules by considering the costs that airlines will bear from schedule modification decisions (network cost: delay, re-routing, and cancelation costs), fuel cost also needs to be considered. Flight schedule modifications without considering fuel cost yield approximately 5% more fuel consumption. However, this extra fuel consumed can be saved at a price of 29% more network cost (delays and re-routing). It is worth noting that the total fuel cost is greater than the network costs by at least 30 times. Therefore, it is more efficient to focus on reducing the fuel consumed.

From an environmental perspective, Lee et al. (2009) reported that aviation results in 3.5 to 4.9% of the total RF of climate change and that this contribution is expected to increase by a factor of 4 in 2050, which makes aviation emissions a serious and critical issue. Climate change considerations and the commitment to reduce the 2005 emissions by 50% in 2050 will promote SAF use. Transitioning from CAF to SAF will cause airlines to incur more fuel costs, thereby forcing them to reduce their fuel consumption by flying at optimal or near-optimal speeds. However, even with this slight reduction in fuel consumption, airlines still pay approximately 26.6% more for some fuel types and have simultaneously more ATFM costs. Hence, increasing emission taxes is not a feasible solution to force airlines to move toward SAF according to the International Air Transport Association (2019). Although the increased taxes may be good for the environment, they will force airlines to increase ticket prices, which will negatively impact the aviation industry. Therefore, to minimize the economic impact of high SAF prices, policies and regulations are needed to promote their usage. SAFs produced using the FT pathway seem the most appealing to policy-makers from the environmental perspective (average LCA emissions of 0.55 kg CO_{2eq}/L), but are considered to be expensive compared to HEFA, which provides an average of 1.2 kg CO_{2eq}/L. However, low emission SAFs, such as FT-SAFs, may facilitate achieving the long-term goal of a 50% reduction in the 2005 emissions by 2050, subject to the economic viability of low emission fuels to the airlines. The high cost of SAF due to the current production capabilities represents a key obstacle. SAF mass production, low prices and price stability are needed to achieve this goal. For this to be possible, policy-makers need to support research and development activities related to SAF production (Zachmann, 2015). Moderate emission SAFs, such as HEFA-SAFs, can be an intermediate step in reducing emissions that will keep the ATFM network less impacted due to their projected low costs (close to or less than CAF prices) and moderate emissions.

The social carbon cost or the monetary value of climate change or damage caused by one tonne of carbon emissions is crucial to climate policies. It weighs the benefits and consequences of emissions, that is, a cost–benefit analysis (Pindyck, 2019). Our analysis presents the incremental carbon price required to balance emission savings and fuel and network cost increases when moving from CAF to SAF. More emission savings can be achieved when SAF prices are increased and consequently the carbon price increases, as higher carbon price is needed to balance the cost of fuel and network delays and re-routing. We also observe that the incremental carbon prices decrease when the CAF price increases.

The social impact of SAF includes several dimensions, such as human rights, labour, health and safety and community governance. This makes the production country a critical social factor. Local SAF production may result in production-related risks that need to be considered, such as threatened biodiversity, induced land-use change, issues related to land rights and displaced agricultural production (Mayeres et al., 2021; Walter et al., 2021; Goetz et al., 2017; Finkbeiner, 2014). Passengers may not be willing to pay extra for SAF, just for the environmental benefits. However, if the social impact of using SAF is more positive than when using CAF, this may give additional incentive for passengers to select airlines using SAF (Rotaris et al., 2020). The ATFM model presented in this work can be extended to consider social aspects of SAFs upon data availability, where according to Ekener-Petersen et al. (2014) thorough social analysis for SAF types is needed. In addition, SAF clearly results in significant emission savings, but its price and the associated increase in network cost increase the challenges of promoting it. Our findings from the ATFM perspective support the findings of Jiang and Yang (2021), who reported that pushing for SAF while it is more expensive than CAF may not be socially efficient.

7.2. SAF and carbon policies within the ATFM context

The air transport action group, a not-for-profit association responsible for long-term sustainability goals and representing all sectors of the air transport industry, set three targets to protect the environment and reduce emissions. One target was to achieve fuel efficiency of 1.5% annually. The timeline of this target was from 2010 to 2020. The next target was achieving carbon-neutral growth despite the traffic increase. This means that the aviation industry needs to keep the emission levels of 2020 stable. The final ultimate target is to reduce the 2005 emission levels by 50% in 2050 (Adam, 2019). The success in achieving all these targets relies on a four-pillar strategy. One pillar is the use of new technologies such as SAF and new aircraft models. The second is operation improvements through better weight management, optimized speed, reduced distance and less time spent in the air to reduce fuel consumption. The third pillar is enhancing infrastructure efficiency by ensuring sufficient ground capacity to reduce air delays. The last pillar is by using market-based measures, and in particular the policies of emission trading, carbon tax, and government subsidies for sustainable fuels (ICAO Secretariat, 2019). In the analysis presented in this work, we study the trade-offs between using SAF (the first pillar) and ATFM management (the second and third pillar). We also consider the effect of the different policies (fourth pillar). Our ATFM analysis shows that expensive SAFs compared to CAF (as the case of some FT-SAFs, Synthesized ISO-Paraffins and Alcohol-to-Jet SAF) help achieve fuel efficiency targets but significantly increase ATFM network cost and that less expensive SAFs (some FT-SAFs, HFEA-SAFs) improve network efficiency at a very minimal increase in the fuel consumption. The key factors are fuel cost, network density in terms of the number of flights and planned routes, decision flexibility (re-routing set), and network airspace configuration (available capacity).

Emission trading, clean development mechanism and joint implementation are three market-based mechanisms under the Kyoto Protocol, which were adopted in 1997 (United Nations Framework Convention on Climate Change, 2008). Emission trading, also known as emission cap and trade, is a market principle where airlines receive a permit for each tonne of greenhouse gases, which can be traded. The cap limit is reduced annually. If airlines emit less than their allowance, they can save the unused allowances for the next years or sell them to other airlines that exceed their limits (European Commission, 2021). This mechanism allows airlines to reduce emissions for a monetary incentive (United Nations Framework Convention on Climate Change, 2022). In contrast to cap-and-trade policy, which is a quantity mechanism, the carbon tax is a price mechanism that assigns a tax on emissions to reduce the amount of emissions to the desired levels. According to Brueckner and Zhang (2010), the permit price from the cap-and-trade policy and the additional cost from the carbon tax policy can be included in the fuel price; thus, the two policies can be seen as a fuel price taxation procedure. In our work, we present a sensitivity analysis of the fuel price increase to show the impact on the ATFM network decisions. Readers can refer to Brueckner and Zhang (2010) and Kang et al. (2022) for the theoretical and empirical effects on airline output.

Increasing CAF price by 10% is denoted as a "10%-tax on CAF" and corresponds to an emission trading or carbon tax policy equivalent to an increase in the fuel price by 10%. A 10%-tax on CAF reduces the fuel consumption and, consequently, the emissions in the case of cancellation (and in the case of no cancellation) between 0.003% and 0.236% (0.007% and 0.008%) at the expense of increasing the ATFM network cost between 0% and 15.0561% (0% and 0.597%). Note that when cancellation is allowed, emission savings can also be achieved by reducing the number of flights resulting in higher ATFM cost (mainly from the cancellation penalty) than in the case of no cancellation. Moreover, comparing SAF with a 10%-tax on CAF showed that Synthesized ISO-Paraffins, Alcohol-to-Jet and a few FT-SAFs result in a higher reduction in fuel consumption than a 10%-tax on CAF under the two scenarios (with and without flight cancellations), which supports the fuel efficiency goal established by the air transport action group (Fig. 12). These SAFs remain more efficient than a 10%-tax policy when flight cancellation is not allowed. Other SAFs tend to reduce the ATFM costs at the expanses of slightly increasing the total fuel consumption (Fig. 12). Note that in all cases, emission savings from SAF are significantly higher than savings from a 10%-tax on CAF (equivalent to CAF with emission trading or carbon tax policy) due to SAFs' low emission factors.

A 10%-tax on SAF (that is, SAF with emission trading or carbon tax policy of an equivalent 10% additional price on the fuel) results in an average of 0.007%, 0.901% and 0.004% reduction in the fuel consumed when considering the cost model, cost and emissions "bi-objective" with cancellation model, and bi-objective without cancellation model, respectively (Fig. 11). This reduction is associated with an increase in the ATFM cost by 0.713%, 47.2% and 0.367% for the three configurations, respectively (Fig. 11). It can be observed that under a tax or emission trading policy, SAF tends to reduce fuel consumption and increase ATFM costs more than CAF. Readers can refer to Tables 1 and 2 in the Supplementary Material for the changes associated with each fuel type. When considering SAF with carbon tax or emission trading policy, changes in fuel consumption levels and ATFM costs follow the same trend as the SAF subsidization scenario, except that fuel consumption changes remain somewhat stable for less expensive SAF (up to 1.2 €/L) when cancellation is permitted (Fig. 13). The higher the tax, the greater the changes when the original SAF's price is high. Since this paper aims to analyze the impact in the context of the ATFM network, we consider the short-term trade-offs (operational level). Considering CAF as a benchmark point, agricultural resides FT SAF, herbaceous energy crops FT SAF, and alcohol-to-jet SAF from forestry residues under a 10% subsidy outperform a 10%-tax on CAF in the fuel efficiency in the bi-objective with and without cancellation configurations (Fig. 14). Other SAFs tend to enhance the efficiency of the ATFM network at most 2.4% at the cost of increased fuel consumption by a maximum of 0.04%. Readers may refer to Fukui and Miyoshi (2017) for the discussion about the long-term rebound effect of fuel price on emission levels. In summary, SAF helps airlines lower their emission levels, thus, requiring fewer purchases of permits or having more permits to sell. Fuel, ATFM network, and permit costs are three crucial factors. It is worth noting that the permit cost and related trade-offs are out of the scope of this work as we focus on the network level.

Our results show that the impact of SAF subsidy is affected by the focus (i.e., the objective function). For instance, SAF subsidy does not affect network delays and fuel consumption if the primary focus is to reduce emissions (cost is ignored). However, the consumption level changes with subsidization if the primary focus is on cost or both cost and emissions (bi-objective configuration). A 10%-SAF subsidy increases the total fuel consumed between 0.005% and 0.020% (based on the SAF type) but reduces the network cost between 0.218% and 0.713% if the focus is on the cost only (Fig. 11).

Assume now that both cost and emissions have equal importance. In that case, we observe from Fig. 11 that the total fuel consumed may increase in the case of cancellation (the case of no cancellation) between 0.328% and 1.577% (0% and 0.009%) to reduce the total network cost between 14.2% and 49.1% (0% and 0.592%). Readers can refer to Tables 3 and 4 in the Supplementary Material for the changes associated with each fuel type. Thus, for some SAF types, a 10%-subsidy may not affect the ATFM network (i.e., no increase in the fuel consumption and consequently the total emissions) but can make SAF more viable compared with CAF. Note that, although the increase in fuel consumption means increasing emission levels, this increase is measured with respect to the case of using SAF without subsidization. Thus, with the slight increase in total consumed SAF, it emits less than CAF. Note also that SAFs with similar fuel prices show similar behaviors (e.g. Camelina and Palm oil HFEA-SAFs) despite the difference in the

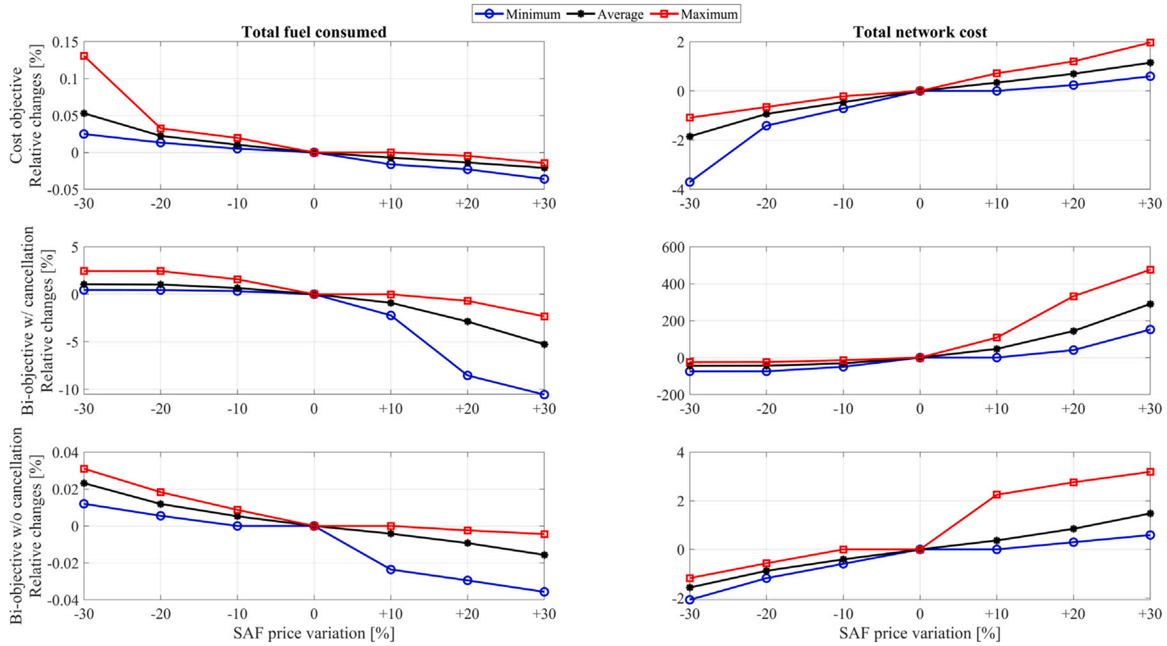


Fig. 11. Relative changes in the fuel consumption and ATFM cost when varying SAF price for different objective functions.

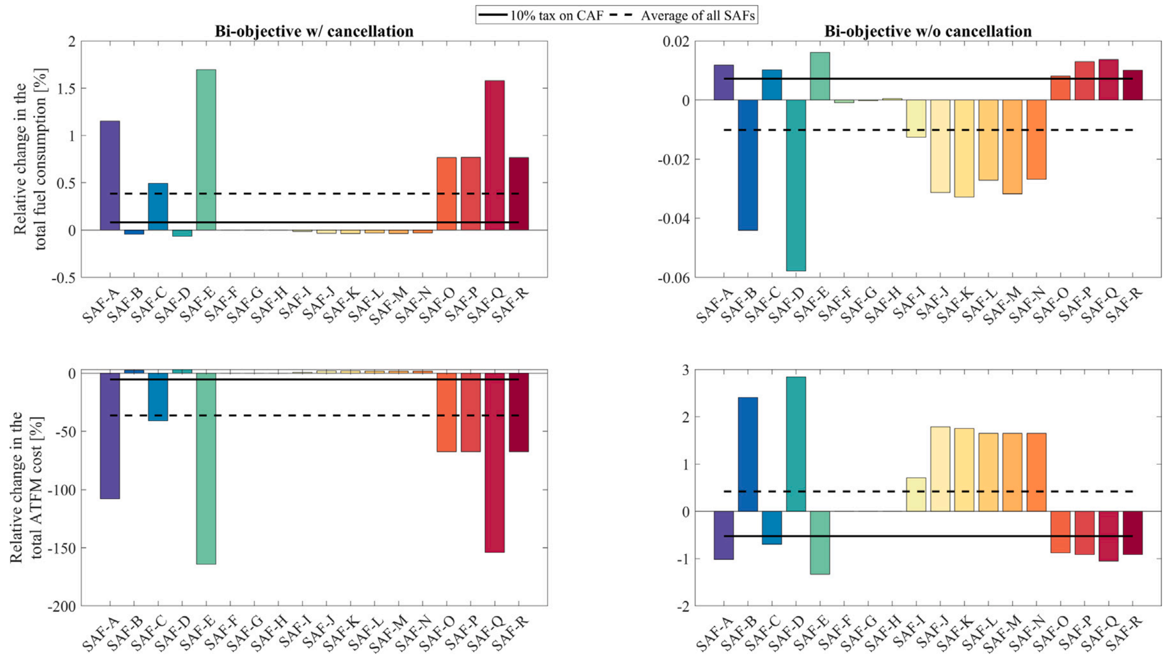


Fig. 12. Relative changes in the fuel consumption and ATFM cost with respect to CAF for the different SAFs and a 10%-tax on CAF. Positive changes indicate a better performance than CAF.

emission factor. In a configuration where flight cancellation is permitted, less expensive SAFs (up to 1.35 €/L) have more stable consumption behavior (i.e., low increase in the fuel consumption) when SAF receives a subsidy from the government (Fig. 13). This stable behavior is also reflected in the ATFM cost changes. The changes in the ATFM network and consumption levels are relatively small and stable in the case in which flight cancellations are not permitted. Mayeres et al. (2021) shows that adding a tax on CAF may also increase the use of SAF, reducing the emission. Additionally, if the government subsidizes SAF prices, SAF prices become more attractive, pushing the transition from CAF to SAF and lowering emissions. Our work includes the impact on

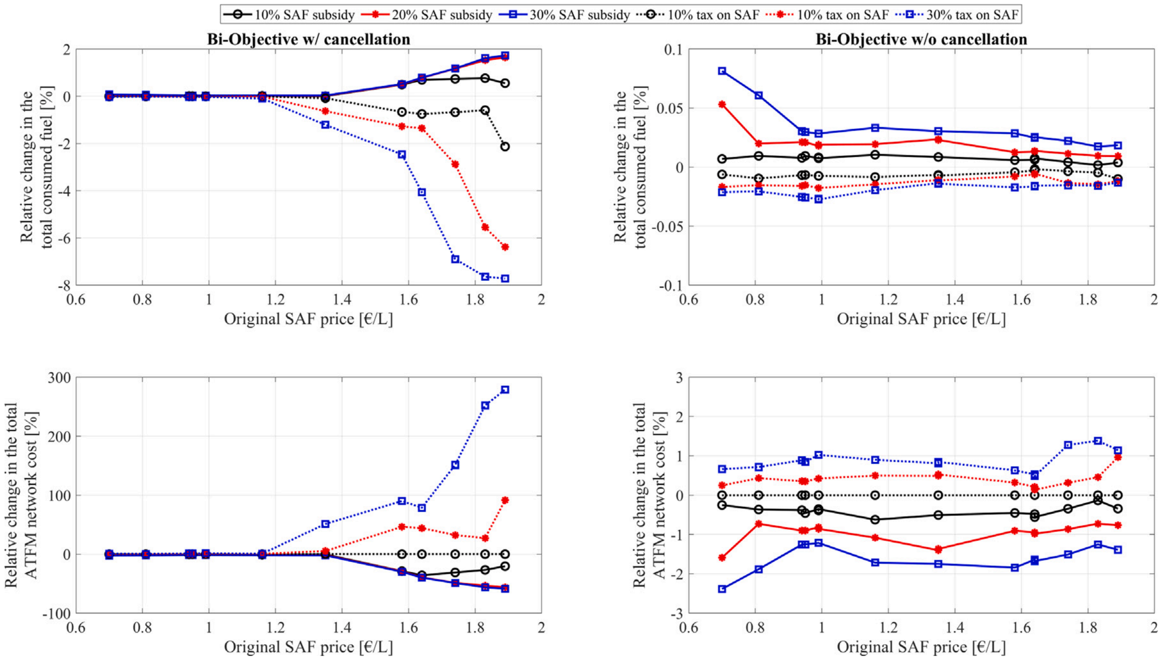


Fig. 13. Average relative changes in fuel and ATFM cost based on the sorted original SAF prices for SAF subsidy and tax cases.

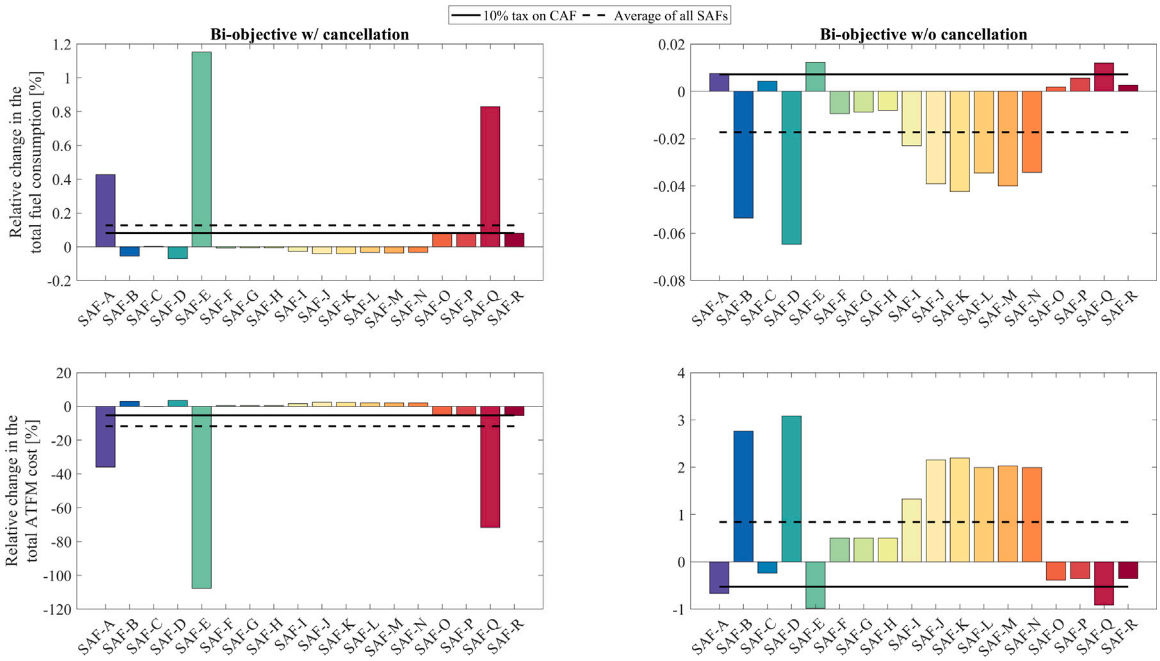


Fig. 14. Relative changes in the fuel consumption and ATFM cost with respect to CAF for the different SAFs with a 10% subsidy and a 10%-tax on CAF. Positive changes indicate a better performance than CAF.

the ATFM network using SAF. A mixed mandate combines the effects of the tax policy and the SAF production subsidization, which means that the mixed mandate acts as a CAF tax to push airlines toward using more SAF and the revenues generated push for lower SAF supply prices. Although for the sake of studying the impact on the ATFM network, we consider a context where either SAF or CAF is used, we consider the transition from CAF to SAF (Fig. 10 and the analysis in Section 6.3). In this analysis, we show that by optimizing the ATFM network decisions under some circumstances, fuel consumption can be lowered.

Table 6
Estimated maximum SAF price [€/L] (percentage increase in the SAF price compared with CAF) under each carbon price assumption with respect to different CAF prices.

Scenario (Carbon price [€/tonne of CO_{2eq}])	C^{CAF}	SAF-A	SAF-C	SAF-E	SAF-O	SAF-P	SAF-Q	SAF-R
	1.215	1.34 (9.32)	1.328 (8.5)	1.347 (9.83)	1.304 (6.83)	1.314 (7.52)	1.329 (8.55)	1.279 (4.97)
	1.283	1.401 (8.44)	1.393 (7.9)	1.407 (8.86)	1.368 (6.25)	1.377 (6.89)	1.389 (7.7)	1.344 (4.57)
High (33)	1.35	1.462 (7.64)	1.457 (7.35)	1.467 (7.97)	1.432 (5.71)	1.441 (6.31)	1.45 (6.91)	1.409 (4.17)
	1.418	1.523 (6.9)	1.522 (6.85)	1.526 (7.14)	1.495 (5.21)	1.504 (5.78)	1.511 (6.17)	1.473 (3.79)
	1.485	1.584 (6.27)	1.587 (6.45)	1.587 (6.43)	1.56 (4.81)	1.569 (5.34)	1.572 (5.54)	1.539 (3.49)
	1.215	1.288 (5.66)	1.273 (4.56)	1.298 (6.39)	1.263 (3.78)	1.268 (4.19)	1.285 (5.43)	1.249 (2.69)
	1.283	1.349 (4.92)	1.338 (4.13)	1.358 (5.54)	1.327 (3.34)	1.332 (3.7)	1.346 (4.7)	1.314 (2.39)
Low (16.5)	1.35	1.41 (4.24)	1.402 (3.73)	1.417 (4.75)	1.391 (2.92)	1.395 (3.25)	1.406 (4.02)	1.379 (2.1)
	1.418	1.471 (3.61)	1.467 (3.37)	1.477 (4.03)	1.454 (2.53)	1.459 (2.83)	1.467 (3.38)	1.444 (1.81)
	1.485	1.533 (3.1)	1.533 (3.11)	1.538 (3.42)	1.519 (2.23)	1.523 (2.51)	1.529 (2.85)	1.509 (1.59)
	1.215	1.267 (4.13)	1.251 (2.91)	1.278 (4.96)	1.247 (2.53)	1.25 (2.8)	1.268 (4.14)	1.237 (1.76)
	1.283	1.328 (3.45)	1.316 (2.56)	1.338 (4.16)	1.311 (2.14)	1.314 (2.38)	1.328 (3.46)	1.302 (1.51)
Very low (10)	1.35	1.389 (2.83)	1.381 (2.23)	1.398 (3.43)	1.374 (1.78)	1.377 (1.98)	1.389 (2.83)	1.367 (1.26)
	1.418	1.45 (2.25)	1.445 (1.93)	1.458 (2.75)	1.438 (1.43)	1.441 (1.61)	1.45 (2.23)	1.432 (1)
	1.485	1.512 (1.79)	1.511 (1.73)	1.518 (2.19)	1.503 (1.18)	1.505 (1.34)	1.511 (1.75)	1.497 (0.82)

The clean development mechanism and joint implementation are emission reduction mechanisms in the Kyoto Protocol managed by the United Nations. The main difference between them is that under a clean development mechanism, projects are initiated in developing countries to support their environmental efforts and provide efficiency. Under joint implementation, projects are initiated in other developed countries (Federal Ministry for the Environment, Nature Conservation, Nuclear Safety and Consumer Protection, 2022). These two mechanisms facilitate the use of carbon credits in verifiable and reliable projects under offsetting schemes. Under an offsetting scheme, purchasing carbon credits in other industries compensates for excess emissions. By buying carbon credit on the open market, airlines compensate for the emissions that they cannot reduce by equivalent reduction in other areas. For instance, under CORSIA, companies are expected to pay less in the carbon market when using SAF, as their offsetting amount is calculated after deducting the benefit of using SAF. The carbon price is assumed to be €33 per ton of CO_{2eq} in 2035 (under a high assumption scenario) (International Civil Aviation Organization, 2019c). Our analysis showed that the carbon price required for SAF to be a viable option is much higher, between €69.7 and €169.3 per ton of CO_{2eq} depending on the fuel type used. This is two to five times greater than that assumed under CORSIA.

ICAO lists the estimated carbon price under three assumptions: high, low, and low (International Civil Aviation Organization, 2019c). Table 6 presents the maximum SAF price such that the SAF remains profitable under each CAF price and for each carbon price assumption. It also shows the maximum increase in the SAF price with respect to the CAF price to remain profitable under a given carbon price. It can be seen from our analysis that a SAF price of €1.41/L for a CAF price of €1.35/L can make the carbon price of €33 per ton of CO_{2eq} profitable. This means that the price of SAF can be, at most, 4.17% higher than the price of CAF to be viable when considering the ATFM network costs compared to 11% based on the benefit–cost analysis without considering network delays, as reported by Lu (2018). Our analysis shows that, on average, SAF cannot be more than 2.1% and 1.26% more expensive than CAF to remain the preferable option at low and very low carbon prices. The analysis by Mayeres et al. (2021) showed that reaching a minimum SAF share of 3.5% or 5.25% is five to ten times costlier than an emission trading policy such as CORSIA. They also found that when the carbon price is low under CORSIA, the current price of SAF makes it an economically nonviable option in the short term. This finding coincides with our analysis for low and very low carbon prices. According to the International Civil Aviation Organization (2019c), carbon prices are assumed to increase every few years; therefore, supporting SAF prices to be between €1.44/L and €1.52/L depending on the fuel type will be optimal when the carbon price increases to €50. In addition, in the early years, regulators need to support SAF prices by supporting large-scale production of SAF. A similar conclusion is observed by Jiang and Yang (2021) when comparing different emission policies using a simple economic model. Since SAF will push airlines to fly near optimal speed resulting in more network delays and re-routing, governments can offer more network flexibility for companies using SAF. From the ATFM network perspective, delay programs can prioritize flights operated using SAF to help airlines compensate for high fuel costs. In addition, fewer penalties can be given to flights using SAF to minimize fuel consumption. For instance, expensive fuel leads to a slight increase in re-routings to achieve lower fuel consumption and avoid delays. Thus, a flexible re-routing scheme with fewer re-routing penalties and costs for flights operated with SAF would motivate airlines and support the move from CAF to SAF. Further, reduced route charges for SAF-operated flights can increase the set of alternative routes for several flights and help reduce delays and network costs. Emission policies should be stable, long-term and focus on SAF's social, environmental and economic benefits to better commercialize SAF (Martinez-Valencia et al., 2021). In addition, if no incentives are offered to airlines, customers and end-users may experience higher ticket prices. Consequently, if the increase in ticket prices is not followed by innovative marketing strategies to attract passengers, airlines can lose their price competitive edge. According to Berger et al. (2022) customers are remarkably unwilling to pay for offsetting CO_2 emissions, which can significantly affect the success of emissions policies.

Although airlines benefit the most from SAF when its price is less than CAF without significantly impacting the ATFM network decisions, a slightly high fuel price can boost environmental commitments with the right compensation for the increased price or motivation. This high fuel price help reduce consumption and consequently enhances fuel efficiency from the operations point of view, as shown in our analysis. This support the short-term goal of 1.5% average annual fuel efficiency improvement (Aviation Benefits Beyond Borders, 2022). In addition, a slightly higher fuel price with an offsetting policy as CORSIA can be attractive under a carbon market if a suitable carbon price is chosen. Thus, incorporating ATFM network delays and re-routing decisions when analyzing possible emission policies can provide a new path for boosting SAF attractiveness. ATFM decisions (delays and re-routing) are short-term and represents daily operations, while emission policies and SAF impact are long-term. Thus, observing the impact of day-to-day operations, understanding it, and when needed changing it can help achieve better results. For instance, from the ATFM model, knowing that a specific route is busy and may increase delays or fuel inefficiency (due to speed changes) indicates the need to use other airways as scheduled paths to reduce last-minute route change and avoid unnecessary additional fuel consumption. Our analysis showed that the monthly average increase in re-routing is around 3.5%. Considering this finding in the airline strategic plans can inspire airlines shifting to SAF to reconsider their flying paths to achieve savings from last-minute re-routing.

8. Conclusion

In this study, we analyzed the impact of considering SAF instead of CAF on ATFM network performance. We formulated a bi-objective mathematical model for the ATFM network. The model accounts for CO_{2eq} emissions and total cost, including delay cost, re-routing cost, and fuel cost. The model was solved using a scalarization technique. A k-means clustering was then used to cluster the Pareto solutions. The analysis revealed that ATFM models need to consider fuel cost in addition to other network-related costs so that airlines will not pay more for fuel while minimizing network delay. Moreover, the expected SAF prices are too high and would require high carbon prices for airlines to be interested in using SAF to reduce emissions. Policymakers need to support SAF production and introduce regulations to give SAF operators more priority than CAF operators. The study uses ground speed values in the fuel consumption function due to lack of wind speed data or true airspeed data. Upon the data availability, the fuel consumption regression function can be updated and reused in the mathematical model. While SAF prices used in this work are projected values based on published reports and studies, this study helps policy makers understand the impact of fuel price and emission value on the delays and re-routing decisions. It is worth noting that this study is based on projected fuel prices, and for instance if HEFA fuel prices appear to be higher than estimated ones, the network behavior becomes closer to that of Synthesized ISO-Paraffins and Alcohol-to-Jet fuels. Thus, the different fuel types presented in this work act as sensitivity analysis on the fuel price and emissions and can be seen independent from the type. In a future study, it would be engaging to extend this work to observe impact of SAF on the ATFM network under various parameter uncertainties and various airspace configuration and airline design (use of hubs, for example). Comparing the aviation network with SAF against other transportation means, such as high-speed rail, can be another research direction.

CRediT authorship contribution statement

Sadeque Hamdan: Conceptualization, Methodology, Software, Formal analysis, Validation, Data curation, Visualization, Investigation, Writing – original draft. **Oualid Jouini:** Conceptualization, Methodology, Validation, Supervision, Resources, Writing – review & editing. **Ali Cheaitou:** Conceptualization, Methodology, Validation, Supervision, Writing – review & editing, Funding acquisition. **Zied Jemai:** Conceptualization, Methodology, Validation, Supervision, Writing – review & editing. **Tobias Andersson Granberg:** Conceptualization, Validation, Writing – review & editing, Funding acquisition. **Billy Josefsson:** Funding acquisition, Resources, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the University of Sharjah, Sharjah, United Arab Emirates, under grant number 1702040585, and by VINNOVA, the Swedish innovation agency, under grant number 2018-02998.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.tra.2022.09.013.

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