

Exploring Future UDPP Concepts through Computational Behavioral Economics

David Mocholí González
Nommon Solutions and
Technologies
Madrid, Spain
david.mocholi@nommon.es

Rubén Alcolea Arias
Nommon Solutions and
Technologies
Madrid, Spain
ruben.alcolea@nommon.es

Ricardo Herranz
Nommon Solutions and
Technologies
Madrid, Spain
ricardo.herranz@nommon.es

Abstract— This paper presents an agent-based modelling (ABM) approach aimed at enabling a rigorous and comprehensive study of flight prioritization mechanisms in the context of demand and capacity imbalances. The implemented model adopts the paradigm of agent-based computational economics, as a particularly suitable framework for the representation of features that are not properly captured by classical approaches, such as bounded rationality or hyperbolic discounting. The main components are described, including a simplified network environment, the agents, the applied behavioral rules and the included prioritization mechanisms: SFP, E-SFP and slot auctioning. Finally, a comparative performance analysis of the prioritization concepts is presented, evaluating their impact on punctuality, cost-efficiency, equity and robustness in the presence of non-rational behaviors. Results show how SFP, counterintuitively, worsens the baseline performance in some scenarios, due to unexpected network effects, while the slot auctioning concept provides the best performance. In general, behavioral biases worsen performance of the mechanisms; however, the auction mechanism results are not significantly affected by the modelled behavioral biases.

Keywords-flight prioritization mechanisms; agent-based modelling; behavioral economics, bounded rationality; hyperbolic discounting; network effects; punctuality; cost efficiency; equity.

I. INTRODUCTION

When a demand-capacity imbalance is predicted during the Air Traffic Flow Management (ATFM) tactical phase, the flights are regulated at airports. Each of the flights involved in the regulation receives a slot (ATFM slot) in a new reference-time list for departure. These slots are currently assigned following the First Planned First Served (FPFS) policy, which is widely accepted by all the stakeholders involved because it minimizes the total delay while preserving equity constraints [1]. However, this solution is far from being optimal from the point of view of Airspace Users' (AUs) cost [2].

Nowadays, AUs are able to swap ATFM slots under certain circumstances. However the level of flexibility provided by this mechanism is rather limited. The User Driven Prioritization Process (UDPP) concept was born within SESAR with the aim of improving existing flight prioritization mechanisms, searching for extra flexibility for AUs in the frame of the Collaborative Decision Making (CDM) philosophy. Some of the

earliest solutions proposed by SESAR UDPP are already being deployed, while newer concepts are currently being investigated [3]. Nevertheless, there is still room for improvement in both the development of advanced mechanisms and the modelling techniques used for their examination.

II. BACKGROUND AND MOTIVATION

Most existing studies about flight prioritization mechanisms make use of normative economic models that predict the behavior of the system under idealized circumstances, such as perfect information and agents' rationality. However, these conditions are often not fulfilled in the real world, where decisions are made in the presence of incomplete or uncertain information, and the rationality is limited.

Agent-based modelling (ABM) presents a way to overcome these issues allowing the observation of the emergent behavior (e.g., network effects) arising from agents' interactions in a bottom-up process [4], combining formality and rigour with the minimization of disadvantages such as strong hypothesis dependency. Generally, an agent-based model is a computer model consisting of a number of software objects, the agents, interacting within a virtual environment. The agents, have a degree of autonomy, react to and act on their environment and on other agents, and have goals that they aim to satisfy.

ABM has prominent synergies with behavioral economics, where deviations from the assumed theoretical behavior play an outstanding role. The convergence of agent-based modelling and behavioral economics into computational behavioral economics provides a natural framework to incorporate behavioral economics insights about human and institutional behavior into operational simulation models [5].

Computational behavioral economics constitutes a particularly suitable framework to represent and simulate market instruments and other flight prioritisation mechanisms. Agent-based modelling has been successfully used to study different types of markets, such as radio spectrum auctions [6] and electricity markets [7]. In the air transport domain, agent-based modelling has been used to study problems such as the use of combinatorial price-setting auctions for primary

allocation of airport slots [8] and the introduction of competition in ATM through the auctioning of licenses to operate en-route air navigation services [9].

III. AGENT-BASED MODEL

A. Overall Description

The model simulates a day of air traffic operations, where the Network Manager takes care of flow management and airlines make decisions on how to deal with the delays imposed in congestion situations. The model comprises three main elements:

- The simulation environment, which provides the network characteristics for the agents to operate in.
- The agents. Two types of agents are considered, representing the main actors of the simulation: the Network Manager and the airlines.
- Exogenous variables, which represent arbitrary external conditions that affect the model but are not affected by it. They include fuel prices and air navigation charges.

The simulation comprises four main stages:

- In the first stage, with some time in advance (e.g., 2 hours), the Network Manager estimates the future demand for all the sectors within a given period of time (e.g., 15 minutes). This expected demand is checked against the corresponding declared capacity, i.e., the number of flights allowed inside that area during the mentioned period of time (occupancy counts). If the Network Manager detects an imbalance between demand and capacity in a certain sector or group of sectors (hotspot), it will initiate a regulation and the excess demand will be displaced over time.
- In the second stage delays are calculated. Flights involved in the hotspot are delayed at the origin airport and assigned new take-off times through ATFM slots. At this stage we distinguish two different resolution paradigms that differentiate some prioritization mechanisms from others: First Planned First Served (FPFS) and Auctions. In the simulations based on the FPFS principle, the Network Manager sequences the flights in the order in which they would have arrived at the constrained airport or sector according to the information included in the filed flight plans. The simulations based on the auction paradigm do not restrict the initial slot position of the flights to any given order; the final sequence of the flights is a result of the successive auctions of all the slots identified inside the hotspot.
- The third stage comprises the airlines' decision process. Once the affected flights receive an initial ATFM slot, the airlines evaluate all possible actions available with the objective of reducing the cost of delay associated with all their affected flights within the hotspot. The number and complexity of airlines' actions depend on the level of flexibility provided by the flight prioritization mechanisms being simulated.
- Finally, the fourth and last stage covers the study and subsequent acceptance or rejection of each of the requests sent by the airlines by the Network Manager. Once this process is completed, the delays are definitive and the airlines can update the flight plans of their affected flights accordingly.

The first stage is repeated iteratively for each of the time windows into which the simulation time is divided. Whenever an imbalance is detected, the second, third and fourth stages are performed. The simulation finishes when the temporal horizon is reached.

B. Simulation Environment

1) Airport Configuration

The defined network consists of 5 different airports, which comprise a mix of hubs and secondary airports.

2) Sector Configuration

The process of sector definition comprises the virtual division of the airspace. Thus, the provision of air traffic services is decomposed into tasks with manageable workload. Our network decomposition in air traffic volumes consists of two different types of sectors. First, 9 en-route sectors are modelled, defining the different airspace structures crossed by the flights after the departure and before landing. Additionally, one extra sector is defined around each airport simulating a Terminal Manoeuvring Area (TMA).

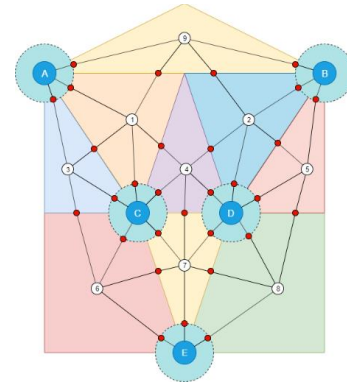


Figure 1. Network topology

An illustration of the resultant network topology is shown in Figure 1. The blue circles define the airports, labelled with letters, the white circles designate the id of each particular sector, and the red dots exemplify the connection entry and exit points between sectors.

3) Route Configuration

The route configuration defined for the model follows a fixed trajectory approach with defined entry and exit points for each sector. The sector configuration is built in such way to allow 3 possible disjunctive trajectories for each OD pair, which only share the departure and arrival sectors (i.e., the airport TMAs).

4) Network Calibration

The topological description of the network needs to be translated into a physical representation. Each of the lines connecting the nodes in the topology diagram (route trajectory) needs to be assigned a distance. Additionally, air navigation charges need to be modelled in order to cover the services provided by Air Navigation Service Providers (ANSPs) over a portion of airspace, in our case coincident with the defined sectors. With the ultimate objective of getting realistic values of cost and distances for each of the routes, we have considered each airport to be a representation of a real airport in the ECAC area. Consequently, the unit rate factor of each charging zone (sectors) and the route distances can be approximated to reality. At the end, the model is calibrated with values such that the 3 different routes between each OD pair are not equal in terms of cost and distance, neither do they present large differences.

C. Agents

1) Agents Characteristics

a) Network Manager

The role of the Network Manager is to apply the corresponding ATFM processes throughout the simulation. It is in charge of the detection of possible demand-capacity imbalances in the air traffic network, as well as of the correct application of the prioritization mechanisms.

b) Airlines

The airline agents are the main agents of the simulation. They make decisions to achieve their objectives according to their internal parameters and the environment. They are modelled as cost-minimizers, but the model allows the modification of their behavior through the inclusion of different biases that depart from purely rational choices.

Airline costs are impacted by air navigation charges (which depend on the distance flown within each sector), the cost of fuel (modelled in a simplified manner, as proportional to the flight distance), and the cost of delay. The calculation of the cost of delay is of special interest for the model because its inherent non-linearity could trigger the use of the available prioritization mechanisms. The costs included in this computation are maintenance costs, crew costs and passenger costs, which can in turn be broken down into soft and hard costs. The maintenance and crew costs are modelled as linear costs and their value is directly extracted from the corresponding tables from the University of Westminster's European airline delay cost reference values [10].

On the other hand, passenger costs show a non-linear behavior over time. The passenger soft costs are often a dominant component in the economics of airline unpunctuality. These are the costs associated with a revenue loss or market value decrease. In order to include them in the delay cost function, the slope values (Euros per minute, per passenger) found in [10] are integrated to calculate the accumulated soft costs at each delay value. Finally, passenger hard costs are due to such factors as passenger rebooking, compensation and care. The modelling of these costs is based on Regulation (EC) No 261/2004 [11] and the Articles 91(1) and 100(2) of the Treaty on the Functioning of the European Union (TFEU).

Flight cancellations are only considered when an airport curfew is missed. In that case, the final departure time of that particular flight is scheduled on the next day and the costs are calculated accordingly by applying the same rules as before.

The simulation scenarios consider 5 airlines classified in two groups, which are differentiated according to their network configuration model:

- Airline 1, Airline 2 and Airline 3: flag carrier airlines with a hub-and-spoke network configuration.
- Airline 4 and Airline 5: low-cost airlines with a point-to-point network configuration.

2) Agent Interaction Rules

Depending on the flight prioritization mechanism evaluated in the simulation, the sequence of agents' decisions and actions follows a different pattern. This variety of interactions can be divided into two main paradigms depending on how the Network Manager originally imposes delays in the context of a demand-capacity imbalance.

a) First Plan First Served (FPFS) Paradigm

The FPFS principle ensures that the affected flights within a hotspot are ordered according to the estimated time over (ETO) the specific sector. The delays imposed to the ordered flights are then sent to the airlines as an initial endowment from which to study a possible prioritization. The main actions performed by each agent are schematized in the Figure 2. It should be noted that the possibility of requesting a rerouting has been included, within this resolution framework, as a step prior to prioritization, with the intention of being more faithful to the real process of actual ATFM operations.

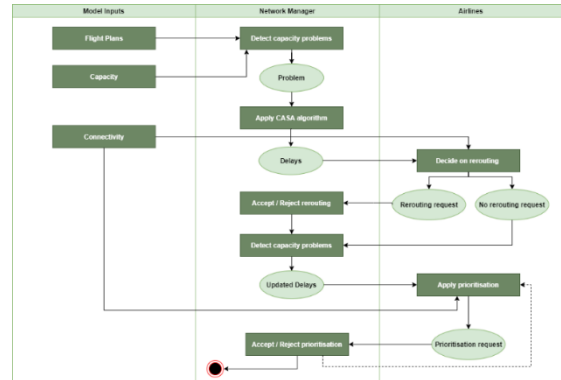


Figure 2. FPFS workflow

Due to the abstraction of all ATFM processes in the figure of a single agent (Network Manager), some measures are simplified. In the model, a flight cannot occupy an ATFM slot if this creates an additional demand-capacity problem in an already resolved time window. When due to this restriction a flight cannot occupy a certain hotspot position, in order to respect the FPFS principle, that position is left empty and the next slot is checked, inevitably worsening network efficiency.

b) Auction Paradigm

Unlike the mechanisms based on the FPFS principle, in an auction the ATFM slots are not filled following the ETO of the specific sector, but the sequence is the result of the amount of money airlines are willing to pay to occupy each of the auctioned slots. The workflow illustrating the whole process is depicted in Figure 3. The implemented auction is a Vickrey auction, which is a type of sealed-bid auction. Airlines submit written bids without knowing the bid of the other participants in the auction. The highest bidder wins, but the price paid is the second-highest bid. This type of auction is strategically similar to an English auction and gives bidders an incentive to bid their true value [12].

Given the limited resources of this first exploratory study, it was decided not to include the airlines' rerouting capability within this resolution paradigm. Consequently, AUs only have the flexibility offered by the auction to face the ATFM delays imposed.

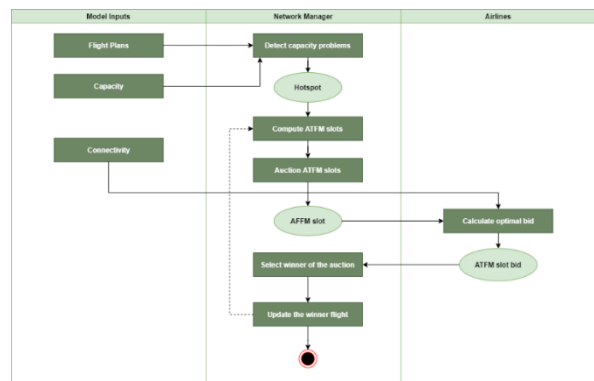


Figure 3. Auction workflow

D. Simulation Inputs

1) Flight Schedule

A flight schedule is required to provide all the necessary information for the Network Manager to perform ATFM functions. It includes all the flights involved in the simulation and provides the necessary information about the origin and destination of the flight, a flight code, the operating airline, the type of aircraft used, and an aircraft identifier. In this study, this data has been synthetically generated from real data. To recreate a realistic level of traffic in our model, the flight schedules of a subset of 5 European airports have been reconstructed from the information contained in the the last filed flight plan contained in EUROCONTROL's Demand Data Repository 2 (DDR2) for a random traffic day.

From all the selected flights, the various operating airlines are grouped by alliances. According to the flight network configuration and the identified alliances, three artificial flag carrier airlines (Airlines 1, 2 and 3) are considered for the model. Finally, with the intention of including an additional point-to-point network configuration, characteristic of low-cost airlines, a series of extra flights were manually added to the schedule. Two artificial low-cost airlines (Airlines 4 and 5) are considered for the operation of these set of flights.

2) Capacity Configuration

The declared capacity of each of the sectors defining the network needs to be modelled. This capacity depends on a complex combination of factors such as traffic flow direction, coordination procedures, in-sector flight times, etc. For the sake of simplicity, the capacity estimation in our model is only based on the expected demand. Given the flight schedule previously generated, the expected demand values per sector and time window are computed. With that information, the capacity values are set following a sliding windows approach: the capacity of a sector during a certain time window is equal to the maximum expected demand for the next 5 time windows. Then, the user is able to manually change capacity values to simulate capacity shortages and generate hotspots.

3) Passenger Connectivity

The SESAR project POEM (Passenger-Oriented Enhanced Metrics) evidenced that passenger-centric metrics are needed to evaluate the full impacts of operational changes [13]. Modelling passenger connectivity is required to evaluate the impact of different prioritization mechanisms on the passengers.

For the experiments described in this paper, a configuration file was artificially generated with all the information regarding passenger connectivity, according to the following assumptions: (i) only flag carrier airlines have connections; passengers can only have a maximum of one connection in their journey; (ii) the waiting time between connecting flights lies between 45 and 120 minutes; (iii) connections are only between flights operated by the same airline; (iv) the total number of connecting passengers inside a particular flight that will take a second flight later is computed as 20% of the total number of passengers on the actual flight who have not made a connection yet; (v) in the event that the connecting passengers inside a flight take different second flights, the number of passengers going to each one of these next flights is randomised.

IV. IMPLEMENTATION OF FLIGHT PRIORITIZATION MECHANISMS

Four flight prioritization mechanisms have been modelled: Slot Swapping, Selective Flight Protection, Extended-Selective Flight Protection, and Slot Auction.

A. Slot Swapping

This mechanism is taken as our baseline scenario because it is currently available to airlines in real operations. It offers the possibility of exchanging the position of two flights belonging to the same airline and affected by the same hotspot as long as no flight occupies a 'before schedule' position after the swap. An airline using the slot swapping mechanism will take the following actions:

- Identify all its flights involved in the hotspot and their associated data.
- Identify all available slot swap possibilities between them.
- For the slot swaps that comply with the schedule restrictions:
 - Compute the cost of delay associated with the baseline for each flight involved in the swap.
 - Perform the swap and calculate the new delays and their associated cost.
 - Compute the cost difference between the baseline cost of delay and the new computed cost.
- Based on the study of all the possible swaps, choose the best option and send the request to the Network Manager.

The Network Manager has no action in this scheme.

B. Selective Flight Protection

The SFP mechanism, developed under SESAR's UDPP programme [3], offers extra flexibility for airlines to redistribute the initial FPFS delay imposed on their flights. This mechanism offers the possibility of protecting important flights that due to schedule limitations could not be protected with a normal slot swap. Consequently, it is understood as a complementary mechanism to slot swapping, meaning that for the specific simulations evaluating the SFP, both mechanisms will be active. An airline using the SFP mechanism will take the following actions:

- Identify all the airline flights involved in the hotspot and their associated data.
- Identify all available slot swap possibilities between them.
- For the slot swaps that cannot be performed with the slot swapping mechanism due to schedule limitations:
 - Compute the cost of delay associated with the baseline delay imposed to the flights involved in the swap.
 - Perform the swap and calculate the new delays for the swapped flights and their associated cost.
 - The protected flight, before schedule at that moment, will have to be placed at schedule (zero delay), meaning zero cost.
 - Compute the cost difference between the baseline and the new computed cost.
- Based on the study of all the possible protections, choose the best option and send the request to the Network Manager.

Following the airline's activity, the Network Manager completes the following tasks:

- Identify the protected flight which is placed before schedule.
- Place it at the first possible ATFM slot at schedule.
- Reorganize the flights impacted by the relocation.

C. Extended-Selective Flight Protection

The E-SFP mechanism, a concept proposed in the scope of SESAR's UDPP investigations on new prioritisation features [3], involves the possibility of selecting the slots for specific flights in a hotspot, either by spending credits if the desired slot reduces the delay, or by earning credits if the slot change increases the delay. This process has an impact on other flights, as their preliminary assigned ATFM slots can be taken by the flight that uses this mechanism. In particular, the prioritisation carried out by AUs can have a negative impact on the flights originally scheduled between the baseline position and the new prioritised flight position upstream the timeline, meaning approximately 2 or 3 minutes of extra delay. However, according to AU experts consulted by EUROCONTROL during the development of the mechanism, this negative impact on other airlines can be considered negligible [14]. An airline using the E-SFP mechanism will take the following actions:

- Identify all its flights involved in the hotspot and their associated data.
- Calculate the airline total cost of delay for that ATFM slot arrangement.
- Identify all the possible ATFM slots where each flight could be located according to schedule restrictions and all the feasible ATFM slot combinations.
- Compute the difference in cost between the baseline total cost of delay and the total cost of delay for each combination.
- Compute the needed or earned credits for requesting each combination.
- If the airline has enough credits to request that ATFM slot combination (or if the combination does not consume any credit):
 - Calculate the value of used or earned credits in the combination.
 - Compare this value with the calculated cost difference for each combination.
- Choose the best combination and send the request to the Network Manager.

This mechanism does not require any action from the Network Manager and is implemented so that each airline has an initial number of credits at the start of the simulation. This allocation represents the number of credits that the airline earned the previous days but did not use yet. For the sake of simplicity, the equivalence between delay and credits is set to a constant value of 1, meaning that 1 minute of delay equals to 1 credit, independently of the characteristics of the congested airspace (size, location or temporal scope).

For the proper operation of the prioritization process, it is essential to calibrate both the initial credits and the monetary value that each airline assigns to the credits. Due to the inherent limitations caused by the temporal scope of the simulation (one day), the calibration process was done by defining a series of decision-making behaviors for each airline. The credit values for each behavior were defined by trial and error so as to incentivize airlines to use the prioritization mechanism:

- Conservative: it imitates a behavior where the airline tends to earn credits by absorbing delay when not very important flights are affected in order to use them in the future in more valuable flights. The monetary value assigned to the credits is significant and the number of initial credits is high. For this case, we have assumed that the airline considers a credit value between 25 and 30 EUR. Only carrier airlines (Airline 1 and Airline 2) are modelled following this behavioral approach.
- Optimistic: it represents a behavior where the airline tends to spend credits, prioritizing not so important flights, rather than to earn credits by absorbing delay. The airline does not expect to need the credits in the future and decides to spend them quickly when it has the opportunity. The monetary value assigned to the credits is low and the number of initial credits is small. For this case, we have assumed that the airline considers a credit value between 10 and 15 EUR. Both, carrier and low-cost airlines have been tested under this strategy (Airline 3 and Airline 4).
- Neutral: it corresponds to an intermediate behavior between the two previous patterns. The monetary equivalence and the number of initial credits values are between the values of the previous levels. Only one low-cost airline (Airline 5) is modelled following this strategy.

D. Slot Auctioning

The formulation of optimal bidding by airlines is the most interesting aspect of this kind of prioritization mechanism. Once again, since the simulation time window of just one day does not allow the implementation of any learning capability or adaptive behavior, airlines are divided according to three levels of action equivalent to those defined for the E-SFP mechanism.

- Conservative: it imitates a behavior where the airline bids aggressively according to a value very close to the worst possible cost situation within the hotspot.
- Optimistic: it represents a behavior where the airline tends to bid lower, in many cases overestimating its ability to win the auction.
- Neutral: it corresponds to an intermediate behavior between the two previous patterns.

The airlines follow the same structure as in the E-SFP mechanism when adopting each of these strategies, Airline 1 and Airline 2 are conservative, Airline 3 and Airline 4 are optimistic and Airline 5 is neutral. An airline participating in the auction of a particular ATFM slot takes the following actions:

- Identify all the airline flights involved in the hotspot and their associated data.
- Collect the actual sequence of ATFM slots in which the hotspot is divided.
- Calculate the cost of delay associated with placing the flight in each of the remaining ATFM slots, from the one being auctioned to the last slot of the hotspot.
- Formulate the bid according to its corresponding behavior:
 - Conservative: the airline bids according to the 75th percentile of the cost distribution calculated in the previous step.
 - Optimistic: the airline bids according to the 25th percentile of the cost distribution calculated in the previous step.

- Neutral: the airline bids according to the 50th percentile of the cost distribution calculated in the previous step.
- Choose the highest bid between the bidding flights and send the bid to the Network Manager.

The money spent by the airlines is redistributed so that the total amount paid by all airlines as direct expenses (air navigation charges plus auction prices) is equal to the total amount of air navigation charges paid by the airlines for the mechanisms based on the FPFS paradigm. This means that all the money that the airlines have spent on the successive slot auctions must be returned to them through some specific mechanism. The approach implemented in the simulation is based on a redistribution proportional to the amount of money spent in charges. Thus, the reduction percentage applied to each airline is equal to the percentage that the same airline has paid in charges over the total amount of air navigation charges paid by all the airlines.

V. BEHAVIORAL ECONOMICS

Behavioral economics provides an interesting option to advance the quality and rigour of simulation models, *inter alia*, by delivering essential understanding of human behavior and decision-making fed by several disciplines (psychology, neuroscience, economics and decision science). Combined with agent-based modelling, computational behavioral economics offers an excellent framework to evaluate flight prioritisation mechanisms under certain behaviors that depart from the purely rational paradigm. These behaviors are included within the decision-making logic of airlines according to the three basic pillars of this discipline: bounded rationality, hyperbolic discounting and prospect theory.

A. Bounded Rationality

The concept of bounded rationality, proposed by Herbert Simon in 1982 [15], is one of the psychological foundations of behavioral economics and provides the idea that human rationality is limited when people make decisions. Rationality is bounded because there are limits to our thinking capacity, available information and feasible time to make the decision.

In capacity-constrained situations, an airline could possibly underestimate or overestimate the value of a flight due to limited available information at the moment of making the decision. The inclusion of this bias in the model is based on a manipulation of the airlines' cost of delay calculation through a random increase or decrease rate. Based on experts' feedback, this parameter was approximated to a value of 15%, although a more thorough calibration is expected for future work. This cognitive bias has been considered in all the mechanisms implemented.

B. Hyperbolic discounting

Intertemporal choice (hyperbolic discounting) is also one of the cornerstones of behavioral economics. The expectation about when a reward is received is as critical as the amount of the reward. Given two similar rewards, humans tend to prefer the earlier reward over the later reward and consequently, earlier (quicker), smaller amounts are often favoured over later, larger amounts, to varying individual degrees [16]. This effect is especially relevant for slot trading, as earlier rewards for letting a slot go may (sometimes only) be spent in the future, and not in the same regulation ('now'). Particularly, in the case where regulations are infrequent, the decision to have a lower flight priority now in order to get a better one in the future can be distorted by such an effect.

This effect has only been identified in the E-SFP mechanism, which allows airlines to release a slot in exchange for credits to spend in the future. In order to include this behavior in the airline's decision process, the monetary value assigned by each airline to their own credits is reduced by a defined rate. This way, airlines are prone to underestimate certain prioritizations due to the undervaluation of the future reward, in this case the credits. The value for that reduction rate was based on experts' feedback and set to 20%. However, as with the bounded rate, a more thorough calibration is expected for future work.

C. Prospect Theory

This behavioral model, introduced by Daniel Kahneman and Amos Tversky in 1979 [17], describes how people make decisions between several alternatives involving risks and uncertainty. The theory exposes the fact that individuals think in terms of expected utility relative to a reference point rather than to absolute outcomes. Prospect theory is developed based on a s-shaped value function representing gains and losses. It is built from a concave part on the gain domain (risk aversion) and a convex piece in the loss domain. As a result, the function behaves much steeper for losses than for gains, which illustrates loss aversion behavior, and constitutes one of the main features of the theory.

In the context of slot allocation, due to loss aversion, an airline can outbid for a slot paying more money in order to avoid losing that position. Of all the prioritization mechanisms implemented, the auction is the one that most clearly fits this cognitive bias. Consequently, the impact of this effect has only been measured in the auction. The method followed consisted in increasing the value of the airlines' slot bids by selecting a higher percentile in the distribution of the cost of delay computed by the airlines, as explained in IV.D. Hence, the conservative airlines bid according to the worst possible position in the hotspot, while the neutral and the optimistic airlines bid according to the 75th and 50th percentile, respectively.

VI. RESULTS AND DISCUSSION

In this section the results obtained from the execution of the simulations are presented. The different simulation scenarios have been defined based on 4 fundamental parameters: level of congestion, prioritization mechanism, behavior scheme, and rerouting capacity. Due to resource constraints, the combinations of these parameters, which generate the scenarios, are limited. The level of congestion remains constant for all the defined scenarios and has been defined through the artificial creation of a series of hotspots, decreasing the capacity of different sectors at different times of the day: in the morning (10:45-11:30), at noon (14:00-14:30), mid-afternoon (16:00-16:15) and at night (19:45-20:15). Additionally, in order to make a fair comparison between the mechanisms based on the FPFS paradigm and the auction concept, which does not include the rerouting option, the former have also been tested without the rerouting option. However, due to time constraints, the behavior dimension is not included for these scenarios with the auction mechanism and the rerouting.

The performance indicators used to evaluate each mechanism take as a starting point the SESAR Performance Framework (SESAR PF), complemented with other specific metrics that are considered relevant for the problem under study. The final set of selected Key Performance Areas (KPIs) from the SESAR PF are: Punctuality and Predictability, Cost Efficiency, and Equity. Additionally, a new KPI, Robustness, is

included with the intention to capture how well different mechanisms are able to cope with the modelled ‘irrational’ airline behaviors.

A. Punctuality and Predictability

From an airline point of view, it is crucial to measure whether a certain prioritization mechanism increases the punctuality of its flights. For airports, the importance of measuring predictability and punctuality lies in the fact that higher predictability levels allow airports to fully use their current capacity. Finally, from the Network Manager perspective, improving predictability and punctuality is one of the goals of the ATFM process.

Predictability and punctuality are merged into one KPA in the SESAR Performance Framework 2018 due to the strong interdependencies between them. However, due to the limitations in the scope of the simulation model, neither the ability of the airlines to change the cost index (change the flight speed) nor the assignments of en-route delays (e.g., holding patterns) are modelled. The only two selected metrics are flight departure delay (PUN1) and passenger arrival delay (PUN2), displayed in Figure 4 and Figure 5 respectively. Hereafter, d stands for delay (flights, passengers) and N refers to the number of elements.

$$PUN1 = \frac{\sum_{i=1}^n d_{flight_i}}{N_{flights}} \quad (1)$$

$$PUN2 = \frac{\sum_{i=1}^n d_{pax_i}}{N_{pax}} \quad (2)$$

Both figures give a clear picture of the influence of rerouting on the level of punctuality measured in the FPFS-based mechanisms. Firstly, for the scenarios with the rerouting option available, it can be observed that the punctuality values offered by the SFP mechanism improve with respect to those offered by the baseline scenario, where only slot swapping is activated. Additionally, it is also noticeable that the credit-based E-SFP mechanism provides the best punctuality results. This induces the idea that a high level of airline flexibility relates with a better optimisation of air traffic.

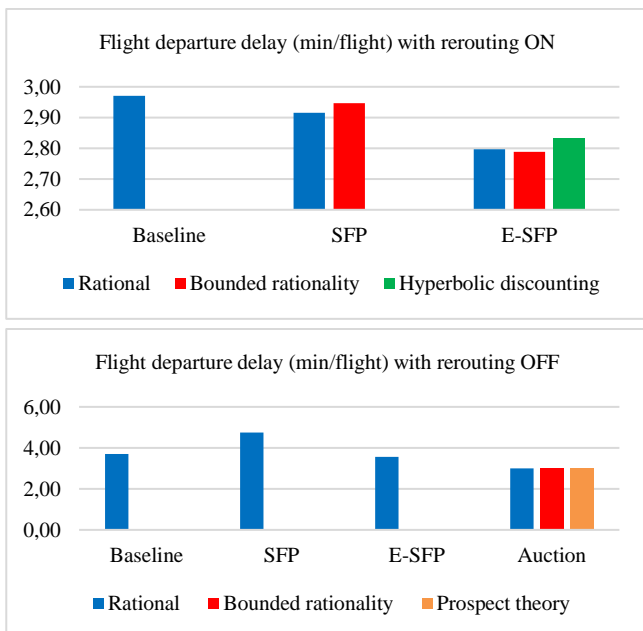


Figure 4. Average flight departure delay

On the other hand, for the scenarios without the rerouting option, although a general worsening of punctuality levels was expected, especially due to the lower level of efficiency of the network, the results offer some insights that at first glance may seem counterintuitive. The SFP mechanism punctuality performance is now the worst of all the mechanisms. Despite offering more flexibility to airlines, the SFP mechanism ends up with worse results than the baseline configuration. The reason is that the extra level of flexibility, which allows airlines to make more optimal requests compared with the baseline scenario, in most cases involves larger alterations in the flight plans of the affected flights. This fact has a direct impact on other flights, which on certain occasions generates downstream network effects and motivates the cancellation of several flights due to curfew. These cancellations explain the drastic deterioration in the punctuality levels for the SFP scenario.

The E-SFP mechanism presents a slight improvement compared to the baseline scenario. The flexibility offered by this mechanism exceeds that of the SFP and, in the same way as before, this is associated with the appearance of network effects due to the high variability of flight demand. However, in this case airlines have more flexibility to solve the problems brought by these network effects, avoiding long delays or possible cancellations, which is accompanied by an improvement in the punctuality performance.

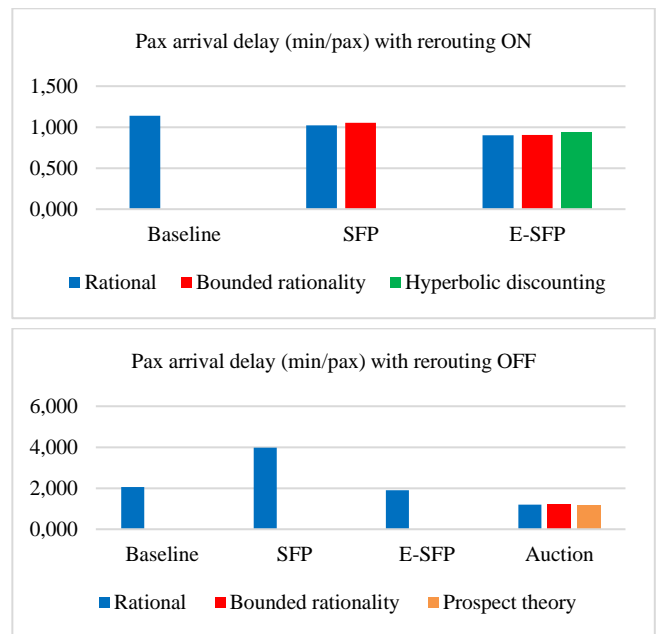


Figure 5. Average passenger arrival delay

Finally, it is very interesting to observe how the auction scenario provides the best punctuality results among all the flight prioritization mechanisms tested without the rerouting option. The auction does not order the flights by the ETO of the specific congested sector but according to how much the airline is willing to pay to win the slot. This paradigm ends up with fewer empty slots because the FPFS order does not have to be enforced and consequently the usability of the network is increased.

Figure 4 and Figure 5 also display the behavioral dimension of the punctuality results. It can be noticed that, as a general rule, the appearance of ‘irrationalities’ inside airline behavior comes with a worsening in the punctuality levels measured by the indicators. However, despite this deterioration, the performance of both the SFP and the E-SFP still improves the results of the baseline mechanism. In the particular case of the auction, the

level of the punctuality is not affected by the modelled behavioral biases.

B. Cost Efficiency

The Cost Efficiency KPA is strongly related to the delay airlines face in their operations and how they manage it. From this perspective, it is essential to measure if a certain prioritization mechanism is able to provide effective tools to decrease the costs associated with the imposed ATFM delay. A mechanism that allows airlines to adjust their operations in a cost-efficient way is also expected to have a positive impact on airports, which can see their income increase due to the greater attractiveness of the system.

The chosen metric to evaluate the cost efficiency of the tested flight prioritization mechanisms is the per-flight cost of delay (CEF1), where $C(d)$ stands for the cost of delay function.

$$CEF1 = \frac{\sum_{i=1}^n C(d_{flight_i})}{N_{flights}} \quad (3)$$

Figure 6 shows a similar trend to that observed for the punctuality indicators. The results for the scenarios with the rerouting on show that the E-SFP mechanism provides the lowest cost of delay per flight, outperforming the values for the SFP mechanism and for the baseline. This confirms the intuition that the cost of delay is directly related to the flexibility provided by the prioritization mechanism.

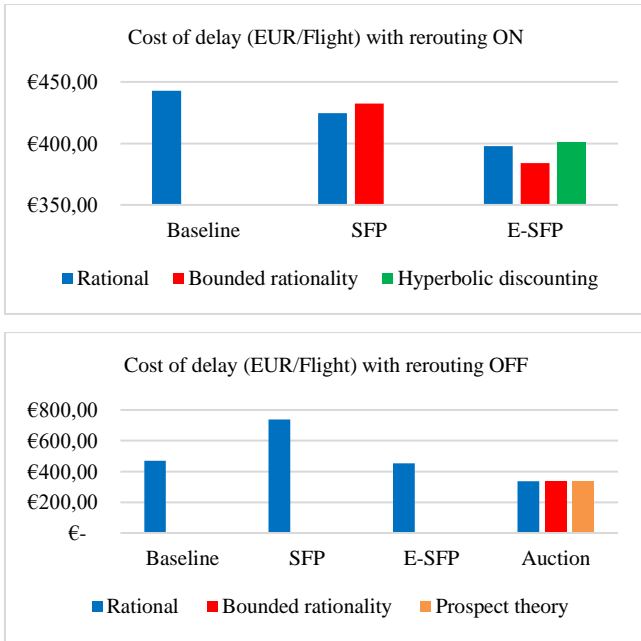


Figure 6. Cost of delay (EUR/Flight)

On the other hand, observing the values for the scenarios without the rerouting option, as anticipated by the punctuality indicators, all the FPFS mechanisms experiment a deterioration in the cost levels. Again, due to the dramatic increase in the flight delay as a result of the cancellations, the cost of delay per flight of the scenario with the SFP mechanism increases considerably and exceeds the values for the baseline scenario.

The E-SFP mechanism also shows a performance consistent with what was previously observed. The extra flexibility provided by this concept allows airlines to make more optimal decisions and, at the same time, to efficiently solve the possible downstream network problems that arise from the prioritizations. Consequently, it improves the cost efficiency results of the baseline scenario. Finally, the auction-based

mechanism provides the best cost efficiency levels, thanks to the better usability of the network.

Figure 6 also displays information of the behavior impact on the cost efficiency performance for each mechanism. It can be noticed that, as a general rule, the appearance of the behavioral biases comes with a small cost increase. However, an unexpected exception is found for the E-SFP mechanism with the bounded rationality model. This can be explained again by the appearance of network effects. Due to the airlines' biased decisions, the simulation ends up with slightly lower average congestion compared to the rational scenario, which, in turn, slightly reduces the cost of delay per flight. Differently, but consistently with punctuality results, the auction-based mechanism is not affected by the different behavioral biases. It will be interesting to assess in future research the sensitivity of these results to more extreme or disparate behaviors between airlines.

C. Equity

Within SESAR's UDPP programme, Equity is considered as a mandatory constraint. A lack of Equity can arise, for example, when one AU receives an advantage or net gain relative to others. This is an essential requirement from AUs' perspective and is closely related with Access, which refers to the need to offer the same prioritization possibilities to all involved AUs.

The metrics selected to measure equity are calculated in relation to a baseline scenario which is understood as equitable. This baseline scenario corresponds to the simulation of the current concept of operations, the FPFS mechanism plus the swapping capability. The subset of chosen metrics are: the change in AU's delay compared with the total change in delay of all the AUs (EQUI1) and the AU delay increment or decrease relative to the baseline total delay (EQUI2).

$$EQUI1_j = \frac{d_{AU_j}^{baseline} - d_{AU_j}^{new}}{\sum_{j=1}^n d_{AU_j}^{baseline} - \sum_{j=1}^n d_{AU_j}^{new}} * 100 \quad (4)$$

$$EQUI2_j = \frac{d_{AU_j}^{new} - d_{AU_j}^{baseline}}{d_{AU_j}^{baseline}} * 100 \quad (5)$$

Due to the disaggregated nature of these indicators (data per AU), equity metrics are analyzed by mechanism. In order to also assess the behavioral dimension of the results, only the scenarios with this component included are presented, that is, scenarios with rerouting for the mechanisms based on the FPFS and scenarios without rerouting for the auction-based mechanism. Some precautions must however be taken when analyzing the results and drawing strong conclusions. In particular, a simulation time of one day is not enough to accurately characterize the behavior of the airlines and especially their learning capabilities. Results could thus be sensitive to the reduced simulation time window and the rigidity of the behaviors imposed on the airlines together with the specific traffic and the network used in the simulation.

Figure 7 shows the equity metrics for the scenarios with the SFP mechanism and the rerouting option available. It is clearly visible that not all the airlines are affected in the same way by the addition of the SFP mechanism. All airlines show a decrease in their associated delay, but there are two airlines in particular that benefit the most from this decrease, regardless their network configuration model. These are Airline 1, a carrier airline, and Airline 4, a low-cost airline. The rationale behind this phenomenon lies in the fact that due to the traffic conditions and

capacity of the model, they are the only airlines that request and use the SFP mechanism. The variations experimented by the other airlines are only the result of the network effects generated by the consequent variability of demand.

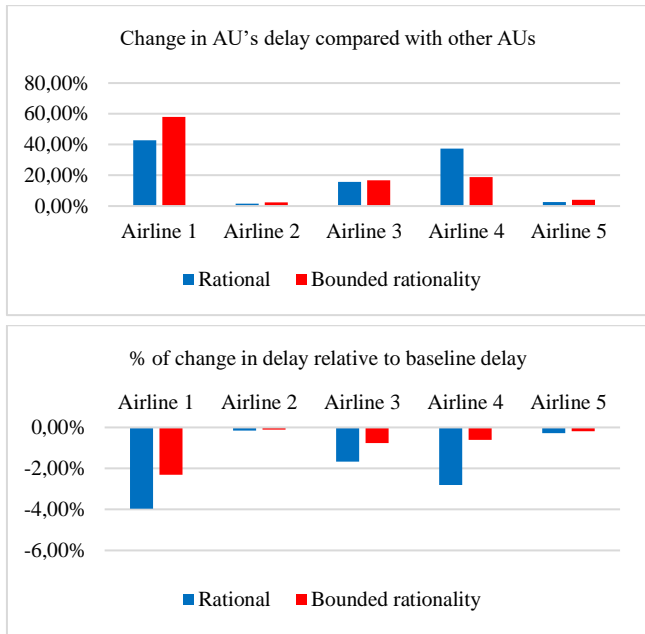


Figure 7. Equity metrics for SFP

Regarding the behavioral impact on the equity levels, it is remarkable to see how the introduction of the bounded rationality model further unbalances the situation towards Airline 1. However, at the same time, the relative improvement in terms of delay level compared to the baseline case is less than before. Due to the bounded rationality bias, the airlines do not make optimal decisions and end up with a lower improvement in terms of delay. Finally, although Airline 1 and Airline 4 are the only airlines clearly benefited from the SFP mechanism, the rest of the airlines are not negatively affected by this fact.

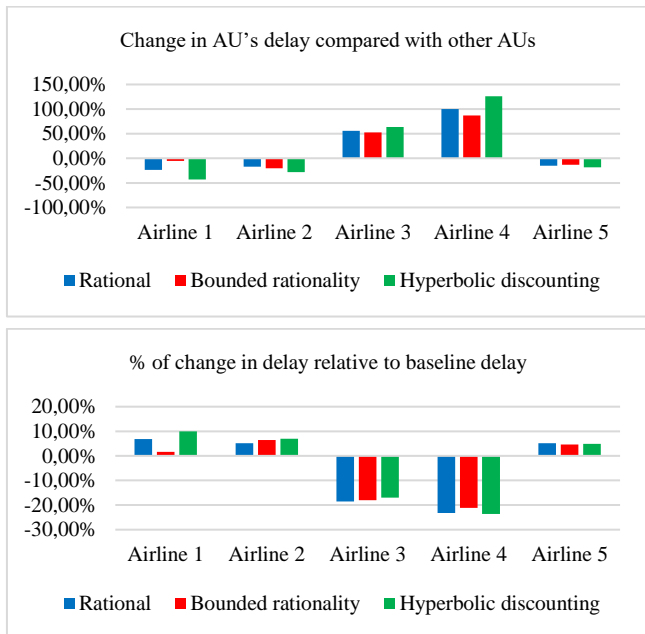


Figure 8. Equity metrics for E-SFP

Figure 8 shows the equity metrics for the scenarios with the E-SFP mechanism and the rerouting option available. The difference between airlines is more evident, including even the worsening of some airlines (Airline 1, Airline 2 and Airline 5). However, this lack of equity should be treated with precaution. Here the results are extremely affected by the tendency of each airline to use or collect credits (conservative, neutral or

optimistic levels) and the partial picture of this behavior (one simulation day). Airline 1 and 2 and Airline 5, characterised by a conservative and neutral behavior respectively, show negative percentages of relative delay change, meaning that they experiment a total delay increase compared to the baseline scenario. This can be explained given the tendency imposed on these type of airlines to collect credits for using them afterwards in more important flights. It is expected that this imbalance across airlines would be reduced by extending the temporal scope to give the airlines more time to use the credits they have earned.

Figure 8 also offers some insights regarding the impact on the equity levels of each behavioral model. The scenario where the hyperbolic discounting bias is applied generates a more unbalanced situation; previously advantaged airlines improve even more their situation and previously disadvantaged airlines slightly worsen their situation. Contrarily, the bounded rationality model shows a tendency to balance the values across airlines, reducing the inequality between them.

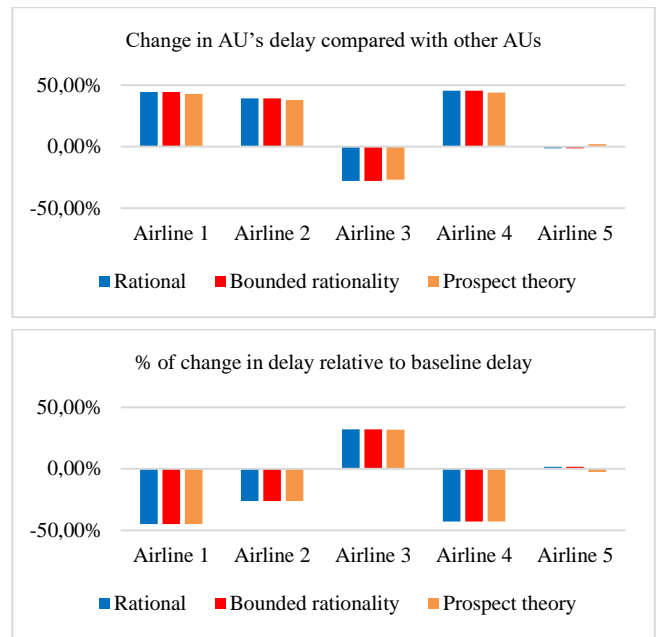


Figure 9. Equity metrics for the Auction

Figure 9 displays the equity results for the scenarios with the Auction without the rerouting option. The values describe a relatively more balanced situation between most of the airlines, with the exception of Airline 3 and Airline 5. The reduction in the total delay observed for all airlines together is distributed almost evenly between Airline 1, Airline 2 and Airline 4. On the other hand, Airline 3 suffers a large increase in delay and a considerable increase in cost compared with the baseline scenario, while Airline 5 is barely affected and presents very similar delay results compared with the baseline scenario.

The results are strongly dependent on the bidding behavior implemented for each airline. However, the case of Airline 3 and Airline 4 is noticeable. Although they are both at an 'optimistic' bid level, meaning they bid way below the worst possible delay cost for their flight, their results are completely opposite. This situation can only be explained by the traffic and network characteristics of the model, which, involuntarily, help Airline 4 to win many more bids than Airline 3, placing its flights earlier in the sequence. Again, the auction performance is barely influenced by the behavioral biases applied.

D. Robustness

Here, the robustness is understood as the ability of a flight prioritization mechanism to maintain the same performance regardless of the degree of irrationality in the behavior of the decision-making agents. The robustness of each mechanism has been assessed by comparing the results of the selected metrics in a rational scenario and the results of the same metrics for other scenarios with certain behavioral biases included.

The robustness of the SFP mechanism is only evaluated against the results coming from the introduction of the bounded rationality bias behavior for scenarios with the rerouting on. It worsens the general performance of the mechanism: the punctuality level drops; the cost of delay increases and the equity metrics show a more unbalanced scenario between the airlines. However, despite this worsening, the SFP performance levels are still above those shown by the baseline scenario.

The E-SFP mechanism has been analysed under two different behavioral models: bounded rationality and hyperbolic discounting. Results show that the mechanism is considerably sensitive to the 'irrationalities'. Surprisingly, the scenario with the bounded rationality bias shows a slight improvement in the performance of the mechanism: the flight delay and the cost of delay drop a little and the equity levels tend to be slightly more balanced. In contrast, the hyperbolic discounting bias worsens all the computed metrics. It seems that the underestimation of the real value of the credit exchanges prevents airlines from realising the full potential of the mechanism.

Finally, the Auction is also evaluated against two different behavioral models; bounded rationality and prospect theory. However, its performance is hardly affected by them. As no extreme situations have been introduced, the operation of the market mechanism remains optimal. In future work, it would be very interesting to test how this conclusion may vary by including more extreme and distinct airline behaviors.

VII. CONCLUSIONS AND FUTURE STEPS

The analysis of the results is challenging due to the great combination of aspects considered for the different scenarios. Despite these difficulties, the following conclusions and insights can be drawn:

- The rerouting option has a strong impact on the simulation and specifically on the selected metrics.
- Surprisingly, the performance of the SFP mechanism worsens baseline results when the rerouting option is disabled. This is related to the network inefficiencies of the strict implementation of the FPFS principle.
- In general, behavioral biases worsen performance. The auction mechanism seems to be the most robust against these biases.
- No mechanism offers a high degree of equity: some airlines benefit more than others, which, sometimes, are harmed compared to their baseline situation.

These results are highly conditioned by the modelling assumptions and require further investigation. The following conclusions and future research avenues can be drawn:

- ABM can be a valuable tool to measure the performance of flight prioritization mechanism and to identify emergent and counterintuitive phenomena.
- Network effects have a strong influence on the results and are very relevant for the evaluation of the mechanisms: a network model is required.

- The results seem to be very sensitive to some modelling assumptions (e.g., lack of reroutings, airline strategies and behaviors, traffic and network definition). Future research should conduct a more thorough sensitivity analysis.

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