Report on agent-based auction model

D4.2

COMPAIR

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COMPAIR

COMPETITION FOR AIR TRAFFIC MANAGEMENT

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Abstract

The increasing air travel demand observed in the last two decades in the European airspace has challenged the actual Air Traffic Management (ATM) system to adapt and respond to the new capacity and congestion issues derived from this growth. The introduction of competition in the ATM sector has been proposed as a means to incentivise the adoption of new technology and more efficient strategies, and thus contribute to the achievement of the European high-level policy objectives for aviation. In this document, we study two possible institutional designs for the introduction of competition in ATM. The first design consists in the tendering of licenses to operate en-route air navigation services in specific geographical areas for a certain period of time. The second, more futuristic scenario consists in the provision of air traffic services on a sector-less, Origin-Destination (OD) pair basis. These institutional designs are investigated by means of agent-based modelling and simulation, which allows us to study the resulting processes from a dynamical perspective, complementing the equilibrium-based approach provided by more conventional approaches such as game theory. We investigate the influence of the different parameters of each institutional design, and the resulting level of technology adoption, the emerging market structure and the air navigation charges up to 2050.

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Executive summary

The goal of the COMPAIR project is to investigate how to introduce competitive incentives in the ATM sector so as to best contribute to the achievement of the European high-level policy objectives for aviation. According to this goal, one of the objectives of the project is the development of simulation models allowing the evaluation of different ATM market designs.

Agent-based modelling offers a way to model socioeconomic systems composed of agents that interact with and influence each other, learn from their experiences, and adapt their behaviours. The global behaviour emerges as a result of the interactions of many individual behaviours, showing patterns, structures, and behaviours that were not explicitly programmed into the model, but arise from the agent interactions.

This deliverable presents the agent-based models that have been developed by COMPAIR to evaluate the outcome of two different institutional designs: (i) the tendering of licenses to operate en-route air traffic services in specific geographical areas and (ii) the provision of en-route air traffic services on a sector-less OD pair basis. We present the simulation experiments that have been conducted and derive a number of conclusions regarding the potential consequences of the proposed mechanisms.

In the case of the tendering of licenses to operate air traffic services in specific geographical areas, the model allows us to explore the impact of different ANSP bidding strategies, showing that a more aggressive strategy aimed to increase market share by sacrificing some profit in the short-term becomes dominant in the long-term. The model also shows that that the bigger ANSPs would have an advantage due to their higher potential to invest in new technology. The maximum market share established by competition regulation has a strong influence on the results: increasing the maximum allowed market share favours the existence of big ANSPs which can obtain economies of scale, but may lead to an oligopoly in the long-term. The order in which the countries are auctioned has a great impact on the local charges of each country, but its global network effect is not so important. Finally, the duration of licenses shows different outcomes, with shorter periods leading to less efficiency gains in the short-term, but higher levels of competition in the long-term.

In the case of the sector-less scenario, with air traffic services provided on an OD-pair basis, we observe that the most efficient ANSPs control an increasing market share until the maximum market share is reached by the ANSPs. The model also shows that, since the dominant ANSPs tend to increase their market share in each auctioning process, the maximum market share allowed is a necessary measure to avoid the emergence of a monopolistic ANSP.

1 Introduction

1.1 Scope and objectives of the deliverable

The general purpose of this document is to provide an in-depth description of the quantitative impact of two different institutional designs described in COMPAIR Deliverable D2.2 [1], targeted at the introduction of competitive incentives in ATM: (i) the tendering of licenses to operate ATC services in specific geographical areas during a period of time and (ii) the provision of en-route air traffic services on a sector-less OD pair basis.

The document is expected to meet a number of objectives:

- present the simulation platform developed for both institutional designs;
- describe the case studies and the different scenarios analysed;
- discuss the main results obtained in the simulations.

1.2 List of acronyms

Acronym	Definition
ABM	Agent-based modelling
ACC	Area Control Centre
ANSP	Air Navigation Service Provider
ATC	Air Traffic Control
ATCO	Air Traffic Controller
ATM	Air Traffic Management
CASK	Cost per Available Seat-Kilometre
GIS	Geographic Information System
OD	Origin-Destination

1.3 Structure of the document

The rest of this document is organised as follows:

- Section 2 provides an overview of agent-based modelling (ABM), its advantages with respect to other modelling paradigms, and its applicability to the COMPAIR project.
- Section 3 presents the model which simulates the tendering of ATC licenses and the main results obtained.
- Section 4 presents the model which simulates the provision of en-route air traffic services on a sector-less OD-pair basis and the main results obtained.
- Section 5 summarises the main conclusions of the study.

2 Agent-based modelling of auction markets: applicability to COMPAIR

Auctions and tendering processes have been widely studied by using game theoretical approaches [3]. However, game theory models are static in nature, which limits their ability to study the dynamics of this type of institutional setting. In recent years, agent-based modelling (ABM) has been recognised as a powerful tool for simulating and analysing complex bidding environments. By using ABM, we can study the evolution of the agents within the simulation, their interaction with their environment and the possible existence of emergent phenomena.

2.1 Overview of agent-based modelling

Agent-based modelling (ABM) can be defined as an essentially decentralised, individual-centric approach to model a system composed of interacting, autonomous agents. Agents have behaviours defined by simple rules (main drivers, reactions, memory, states...) and interact with the environment and with other agents, influencing their behaviours. When running the simulation, the global behaviour emerges as a result of the interactions of many individual behaviours, showing patterns, structures, and behaviours that were not explicitly programmed into the model, but arise from the agent interactions. ABM offers a way to model social systems composed of agents that interact with and influence each other, learn from their experiences, and adapt their behaviours.

2.1.1 Structure of an agent-based model

A typical agent-based model has these three elements [4] (Figure 1):

- A set of agents, their attributes and their behaviours.
- A set of agent relationships and methods of interaction.
- The agents' environment.

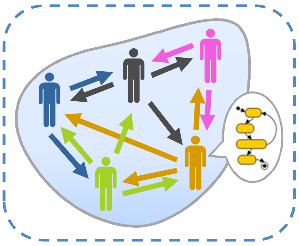


FIGURE 1 – ABM SCHEME

2.1.1.1 Agents

Agents, which can represent people, companies, projects, assets, vehicles, animals, etc., are discrete entities with their own goals and behaviours. The essential characteristics of agents are:

- An agent is a self-contained, modular, and uniquely identifiable individual.
- An agent is autonomous, i.e., it can function independently in its environment and in its interactions with other agents.
- An agent has a state that varies over time.
- An agent is social, i.e., it has dynamic interactions with other agents that influence its behaviour.

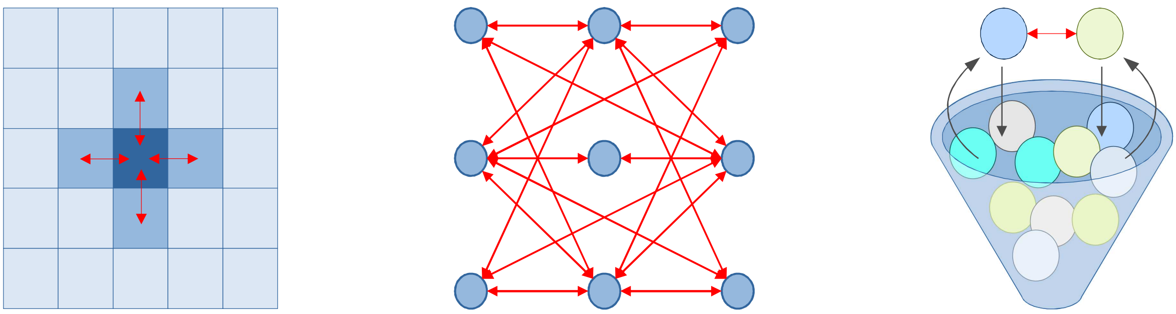
Agents may also have other useful characteristics:

- An agent may be adaptive, by having rules or more abstract mechanisms that modify its behaviour. For example, an agent may have the ability to learn and adapt its behaviour based on its accumulated experiences.
- An agent may be goal-directed, having goals to achieve with respect to its behaviours. This allows an agent to compare the outcome of its behaviour with its goals and adjust its responses and behaviour in future interactions.
- Agents may be heterogeneous.

2.1.1.2 Interactions

One of the main elements of ABM is that only local information is available to an agent. Agent-based systems are decentralised systems, which means that there is no central authority that controls agents' behaviour in an effort to optimise system performance. As in real world systems, agents interact with a subset of other agents, termed the agent's neighbours. Local information is obtained from interactions with an agent's neighbours and from its local environment. An agent's set of neighbours may change as a simulation proceeds.

The way agents are connected to each other is defined by the topology of the agent-based model, which describes who transfers information to whom. Typical topologies include a spatial grid (Figure 2.a), a spatial network of nodes (agents) and links (relationships) (Figure 2.b), or a non-spatial model (Figure 2.c). In some applications, agents can interact according to multiple topologies.



A) SPATIAL GRID B) SPATIAL NETWORK C) NON-SPATIAL

FIGURE 2 – TYPICAL TOPOLOGIES OF AGENT-BASED MODELS (FROM [4])

2.1.1.3 Environment

Agents interact with their environment. The environment may simply be used to provide information on the spatial location of an agent relative to other agents or it may provide a richer set of geographic information, as in a Geographic Information System (GIS). An agent's location included as a dynamic attribute is sometimes needed to track agents as they move across a landscape, contend for space, acquire resources, and encounter other situations.

2.1.2 Added value

Most computational modelling research describes systems in equilibrium or as moving between equilibria. Agent-based modelling, however, using simple rules, can result in different sorts of complex behaviour and allows the examination of how the scenario behaves out of equilibrium, when it is not at a steady state [5]. A more detailed discussion of the benefits of ABM over other modelling techniques ([6], [7]) is included below.

2.1.2.1 ABM captures emergent phenomena

Emergent phenomena result from the interactions of individual agents. By definition, they cannot be reduced to the system's parts: the whole exhibits new properties not observed in the individual elements. Classical examples of these phenomena are the behaviour of bird flocks, fish schools, traffic jams, etc.

An emergent phenomenon may have counterintuitive properties that are decoupled from the properties of the parts. As a result, emergent phenomena are difficult to understand and predict. ABM is, by its very nature, the most accurate approach to modelling emergent phenomena: in ABM, the modeller simulates the behaviour of the system's agents and their interactions, capturing emergence from the bottom up.

2.1.2.2 ABM provides a natural description of a system

In many cases, ABM is the most natural modelling approach for describing and simulating a system composed of behavioural entities. ABM makes the model seem closer to reality. As an example, it is more natural to describe how drivers move than to come up with the equations that govern the dynamics of the density of traffic. Because the density equations result from the behaviour of individual vehicles, ABM will also allow aggregate properties to be studied.

2.1.2.3 ABM is flexible

The flexibility of ABM can be observed along multiple dimensions. For example, it is easy to add more agents to an existing model. ABM also provides a natural framework for tuning the complexity of the agents: behaviour, degree of rationality, ability to learn and evolve, and rules of interactions. Another dimension of flexibility is the ability to change the levels of description and aggregation: one can easily play with aggregate agents, subgroups of agents, and single agents, with different levels of description coexisting in a given model.

2.1.3 Suitability of ABM

ABM will be suitable when some of the benefits previously described are relevant for the study. In particular, ABM will be an appropriate technique in any of the 3 following cases:

1) When there is potential for emergent phenomena:
    - Individual behaviour is nonlinear and can be characterised by thresholds, if-then rules, or nonlinear coupling. Describing discontinuity in individual behaviour is difficult with differential equations.

- Individual behaviour exhibits memory, path-dependence, hysteresis or temporal correlations, including learning and adaptation.
- Agent interactions are heterogeneous and can generate network effects.
- Averages will not work. Aggregate differential equations tend to smooth out fluctuations. This is important because, under certain conditions, fluctuations can be amplified, particularly if the system is linearly stable but unstable to larger perturbations.

2) When describing the system from the perspective of its constituent units:
   - The behaviour of individuals cannot be clearly defined through aggregate transition rates.
   - Individual behaviour is complex. Everything can be done with equations, in principle, but the complexity of differential equations increases exponentially as the complexity of behaviour increases, and describing complex individual behaviour with equations may become intractable.
   - Activities are a more natural way of describing a system than processes.
   - Validation and calibration of the model through expert judgement is crucial. ABM is often the most appropriate way of describing what is actually happening in the real world, and the experts can easily ''connect'' to the model and have a feeling of ownership.
   - Stochasticity applies to the agents' behaviour. With ABM, sources of randomness are applied at the agent level, as opposed to a noise term added more or less arbitrarily to an aggregate equation.

3) When changes are anticipated in the model:
   - The appropriate level of description or complexity is not known ahead of time and finding it requires some tinkering.

2.2 Applicability to COMPAIR

In the COMPAIR project, in which several heterogeneous agents will be analysed (e.g., ANSPs), ABM can provide additional insights compared to classical modelling paradigms, such as the possibility to analyse the temporal evolution of the system, how agents are affected by external factors, and their ability to adapt their behaviour over time.

Among the institutional frameworks proposed by COMPAIR, options 3 (Tender of licenses for en-route air traffic services) and 4 (Flight-centred ATM) seem the most appropriate options to be analysed by means of ABM. Some of the features that would be interesting to analyse are:

- Different behaviours of participants in auctions: each company has its own goals and rules for management actions. Some of them are more conservative and try to maximise profitability, while others may be more interested in increasing their market share and willing to take more risks. Assigning different bidding and learning methods allow us to explore the different results that could be obtained by each type of company.
- Effect of different parameters of the auctions, such as their periodicity, on the dynamics of the system.
- Adaptive behaviour of ANSPs as a function of their current status and necessities.

3 Tendering of licenses to operate en-route air traffic services in specific geographical areas

3.1 Model description

3.1.1 Overall Description

The model simulates the tendering of licenses to operate en-route air traffic services in specific geographical areas and for a certain period of time. It comprises three main elements:

1. Geographical context, which provides the environment for the agents to operate in.
2. Agents. Three types of agents, representing the main actors of the simulation, are considered: the regulator, the ANSPs and the airlines.
3. Exogenous variables, which represent arbitrary external conditions that affect the model but are not affected by it. They include the fuel price, the passenger demand and the technology level, which represents the ratio between the productivity improvement and the investment in technology made by ANSPs.

The simulation consists of two stages (see Figure 3): the first stage simulates the tendering process, in which ANSPs compete for the control of different geographical areas. In this stage, only the regulator and the ANSPs participate. For the sake of simplicity, we are modelling a single airline agent whose goal is to meet the total demand, and no congestion costs are considered. ANSPs submit a certain unit rate per service unit (€/flight-km) per area that will be the maximum unit rate applicable in that area during the license period. Contract conditions in the tendering process include the minimal capacity the ANSPs have to provide during the license period and the maximum market share an ANSP can handle due to competition regulation, in order to avoid monopolistic behaviours.

The second stage simulates how agents evolve between auctions. In this stage, airlines aim to meet total passenger demand and react to the ANSPs decisions by choosing different routes according to the air navigation charges applied by the ANSPs in each geographical zone. Charges are adjusted every given period of time until the license period is over.

Once the license period expires, the tendering process is repeated. This could lead to contract renewal for the incumbent provider or to a new provider supplying the market. Those ANSPs that do not get any area are assumed to go into bankruptcy and disappear from the market. The simulation is finished when the temporal horizon is reached.

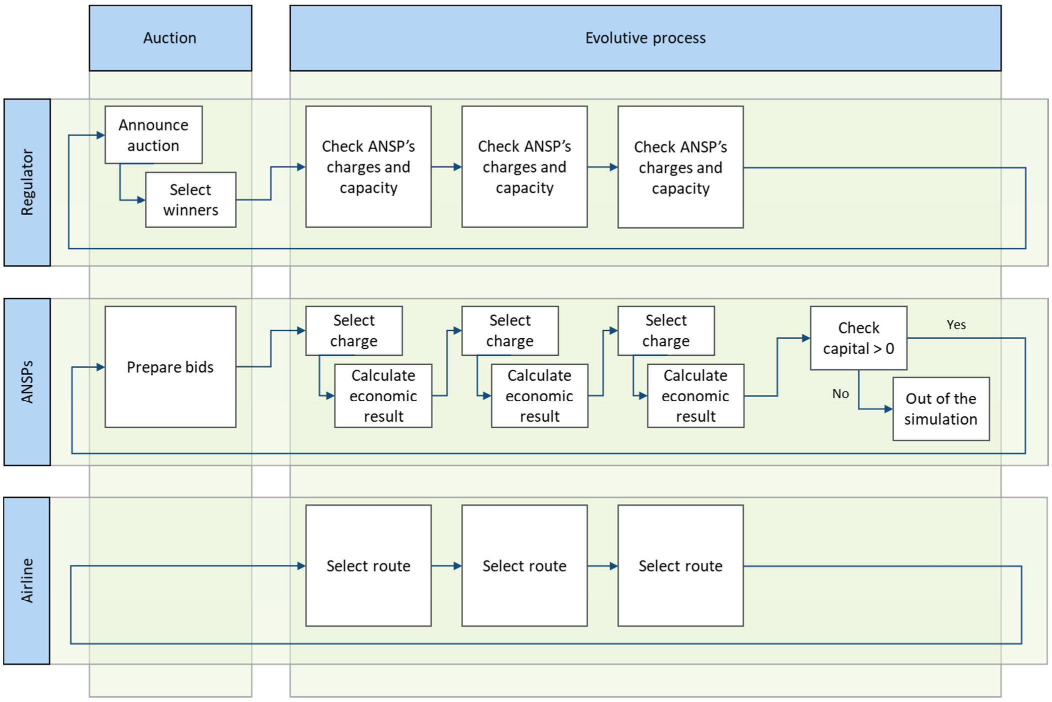


FIGURE 3 – SIMULATION SCHEME

3.1.2 Main assumptions and model restrictions

The following assumptions and restrictions have been considered:

- ATCOs may monitor any flight in any of the charging zones controlled by the ANSP they are working at. We have added this assumption considering that this could be one of the main benefits of liberalisation, allowing ANSPs to adapt their resources more efficiently.
- At the beginning of the simulation, ATCOs working at a specific area ("legacy ATCOs") will maintain their labour agreement throughout the simulation (until retirement). Thus, it is necessary to assume an initial staff, age of the staff and retirement age in each area. The initial staff has been obtained from ACE reports, and we have assumed that the number of legacy ATCOs in each charging area decreases linearly until it is equal to zero in 2045.
- Legacy ATCOs will work at the ANSP controlling their original area until they retire.
- New ATCOs ("non-legacy ATCOs"), who are hired throughout the simulation, will have the same cost regardless of their nationality and will be employed by the same ANSP during all the simulation, unless they are dismissed. This assumption is based on the liberalisation of the ANSPs and the free movement of labour within the EU. Despite the fact that there will still be differences in the future between the countries and this assumption is therefore a simplification, it seems reasonable to assume that one of the outcomes of the proposed market should be a homogenisation of wages across countries.
- When hiring new ATCOs, there is an initial extra cost due to the training.
- When dismissing new ATCOs, there is an extra cost due to dismissal costs.
- ATCOs have the same individual productivity regardless of their country and experience. That is, a German ATCO is as efficient as a French ATCO if they work with the same technologies.

Then difference of productivity between ANSPs is a parameter of each ANSPs that depends on their technology level and not on its ATCOs.

- If the capital of an ANSP during a certain period becomes negative, it goes into bankruptcy and disappears from the market in the subsequent tendering periods.
- There are no new ANSPs entering the market. This is a limitation that could be eliminated in future versions of the model. In the scenarios presented in this study, this should not be particularly problematic, since ANSPs are not endowed with anticompetitive behaviours, and therefore they act as if they could be competing with newcomers.
- For the sake of simplicity, an average plane size, load factor and operational cost per kilometre are considered for all flights regardless of the origin-destination pair.

3.1.3 Model inputs

The following data are required as inputs to configure the model.

- Temporal horizon.
- Maximum market share (defined as the number of flight-km controlled by an ANSP divided by the total flight-km in the network) allowed by competition regulation [0-1].
- Duration of licenses (time between auctions).
- Auctioning order: order in which areas are auctioned when auctioned in the same step. They can be auctioned randomly or depending on their size.
- Schedule of auctions: date on which the first auction of each area takes place
- Areas' geometry and current air navigation charges.
- ANSPs' parameters (see section 3.1.5.1.2).
- Employment costs per non-legacy ATCO-hour, dismissal cost, hiring cost and cost evolution (low, medium, high evolution scenario).
- Minimum profitability expected by the ANSPs
- Set of airports which will be the origin/destination of the flights.
- OD routes. A group of different routes for each OD pair.
- Demand forecast for each OD pair up to 2050. Different scenarios may be analysed (low, medium and high evolution scenario).
- Fuel cost forecast. Different scenarios may be analysed (low, medium, high evolution scenario).
- CASK data (based on actual airline data).

3.1.4 Geographical context

The geographical context (Figure 4) provides the environment for the agents to operate in. It is composed by (i) a set of geographical charging zones that the ANSPs compete to control; (ii) a group of airports representing the main destinations within the charging zones; and (iii) a collection of routes per OD-pair defining the possible paths the airlines can fly.

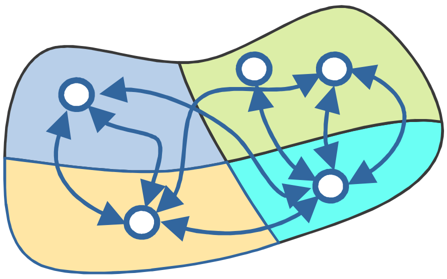


FIGURE 4 – GEOGRAPHICAL CONTEXT

3.1.5 Agents

The model includes three types of agents representing the main actors concerned with the auctioning process: ANSPs, Airlines, and the Regulator. In the following paragraphs we describe the characteristics and the interaction rules of the agents.

3.1.5.1 Agents characteristics

3.1.5.1.1 Regulator

The role of the regulator is to provide and store the public data created throughout the simulation (e.g., the charge of each charging zone), announce the auction parameters (e.g., the minimum capacity) and select the winners of the auctions.

3.1.5.1.2 ANSPs

The ANSP agents are the main agents of the simulation. They make decisions to achieve their objectives according to their internal parameters, their competitors and the environment. In the experiments presented in this document, they are modelled as profit-maximisers, but other objective functions could be implemented, such as revenue maximisation or cost minimisation. This would lead to different results, as discussed in COMPAIR Deliverable D4.1 [8].

The parameters that define an ANSP are:

- Charging zones they control.
- Human resources (number of ATCOs).
- Financial capital. The capital available to the ANSPs to invest either in hiring ATCOs, improving their technology level or paying the costs of dismissing staff.
- Bidding strategy. It defines the learning method that the ANSPs will employ to characterise their competitors' behaviour and calculate their bids (see section 3.1.5.2.1)
- Technology level. Parameter that controls the productivity of each ANSP: the higher the technology level, the more productive are the ANSPs.

3.1.5.1.3 Airlines

The airline agent, which represents the different airlines that fly daily over the European sky, is assumed to be interested in minimising airline costs. Airline costs are impacted by ATC charges, the cost of fuel and the level of congestion [9]. Its objective is to meet the total demand at the minimum possible cost. The operating costs other than the fuel cost and the air navigation charges are modelled as a parameter of these agents.

3.1.5.2 Agents' interaction rules

3.1.5.2.1 Auctioning Process

The sequence of agents' decisions and actions follows the scheme included in Annex I. Tendering simulation scheme - Figure 36, which is schematised in Figure 5.

The Regulator has the role of announcing the auction parameters and allocating the auction areas to the winning bidders.

The ANSPs submit a bid corresponding to the maximum charge that would be applied to the auctioned zone. ANSPs will be allowed to apply lower charges in order to influence demand (competition in the market), but not higher charges. To submit the bid the ANSPs take the following actions:

1. Calculate their total resulting market share in case of winning the auction and evaluate if this meets the condition of the maximum market share allowed.
2. Determine the minimum profitability they want to achieve. This lies between a minimum and a maximum value of the total cost of controlling the network, and it depends on an adaptive factor that takes into account the current status of the ANSPs, according to Eq (4).
3. Estimate in an iterative process the best bid charge by multiplying the current charge by a bid factor. The bid factor ranges from 0.5 to 1.5, in steps of 0.001 to limit the number of calculations. For each bid factor, they: (a) estimate the resources needed according to their technology level and the expected number of flights, calculated based on the passenger demand forecast and the average plane size and load factor; (b) estimate the total expected profit, as the difference between the expected income and cost, and the profitability, dividing the expected profit by the expected cost; (c) obtain the probability of beating their competitors. This is calculated with one of the following learning methods: Friedman and Gates, which characterise the behaviour of all their competitors and estimate the probability of winning the auction accordingly, and Fine, which only characterises the pattern of the winning bids of previous auctions (see Table 1), (d) calculate the auction expected profit, defined as the product of the expected profit by the probability of winning the auction.
4. Submit the bid that maximises the auction expected profit

Once the regulator has allocated the areas to the winning ANSPs, they determine the amount of capital to invest during the following license period in order to upgrade their technology level. For simplicity, in the current version of the model the amount of investment is not a decision made by the agents but is set to 80% of their expected profit in the subsequent license period. In the future, the model could be improved by implementing different strategies for different ANSPs.

As ANSPs invest in new technologies, their technology level increases, they become more productive and their staff requirements are lower, which is reflected in less staff costs in subsequent periods.

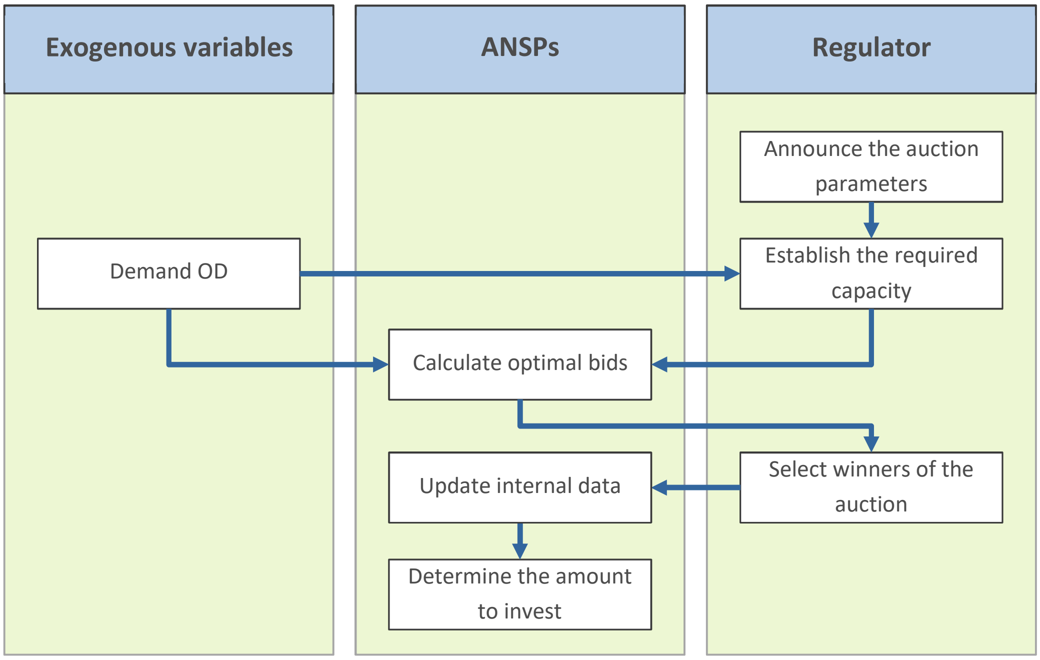


FIGURE 5 – SCHEME OF AGENTS' DECISIONS IN THE AUCTIONING PROCESS

Each step of the process is described in further detail below.

I. Regulator: announce the auction parameters

According to the schedule set, the Regulator announces the areas that are being auctioned and estimates the flight-km in all the areas employing the demand forecast and past data of the routes flown by the Airlines in the last 2 years. This estimation determines the minimum capacity that the winning ANSPs will have to satisfy in the auctioned areas during the following license-period. The estimation of demand per area is also employed to calculate the market share of each ANSP (controlled flight km/total flight km).

The Regulator estimates the demand as follows:

- According to the OD demand forecast, the Regulator estimates the number of flights that will fly each OD pair.
- For each OD pair, the Regulator gets the number of flights that flew each possible route and gets the distribution of flights per route in each OD pair in the last two years.
- Assuming that the distribution of flights per route will be the same as the distribution of flights in the last two years, the Regulator estimates how many flights will select each route r.

$$E(flights_{OD},r) = forecast\_flights\_OD \times \frac{past\_flights\_OD,r}{past\_flights\_OD} \qquad \text{EQ (1)}$$

- Finally, the Regulator calculates the demand (flight-km) in each area using the number of flights per route and the distance that each route flies through each charging zone.

II. ANSPs: check the availability to participate in the auctioning

ANSPs collect the information announced by the Regulator and check whether they can bid or not for the auctioned area depending on the market share.

$$market\_share = \frac{\sum_{\substack{area \in ANSP \\ auctioned\_area}} regulator\_demand_{area}}{\sum_{area} regulator\_demand_{area}} \leq max\_market\_share \qquad \text{EQ (2)}$$

If they can bid for the charging zone, they calculate the optimal bid for the zone in the next step.

III. ANSPs: calculate the optimal bid

This is the core operation of the process. In this operation, ANSPs calculate the bid that maximises their expected profit for the license-period.

The charge bid by the ANSPs is the result of multiplying the winning charge of the previous period (previous charge-cap) by a bid factor. In other words, when bidding for *Area_A*, whose previous charge-cap was *charge_A,* the bid that ANSPs propose is equal to *bid_factor*charge_A.* To calculate the optimal bid, the ANSPs take the following actions:

a) Obtain the minimum profitability they are willing to achieve.

To calculate the profitability, calculated as the profit divided by the cost, the ANSPs take into account their market share, their actual productivity and the maximum productivity they could achieve with given technology. The idea is to calculate an adaptive factor α which considers the situation of the ANSPs in order to adapt their bids and carry out a sensitivity analysis of this factor. For simplification, and since data about the actual profitability desired by the companies is not publicly available, the adaptive factor has been modelled as a function of the current market share of the ANSP, the maximum available market share, the expected demand of the ANSP and the maximum demand the ANSP could control with their resources Eq (4). The lower the adaptive factor, the lower the profitability required by the ANSPs. The underlying logic is that an ANSP which has unused resources (i.e., $E(demand〗\_ANSP))/(max\_demand\_ANSP) \ll 1)$ or a low market share will prefer to get an area in order to increase its market share or employ its resources more efficiently despite having a lower return.

The minimum profitability required by ANSPs, which is between a minimum (*min_value*) and a maximum value (*max_value*) set by the user, is calculated as follows:

A. Calculate the market share if no area is assigned to the ANSP:

This value represents the market share that the ANSP would have if it is not allocated the auctioned area.

$$market\_share_{ANSP} = \frac{\sum_{area \in ANSP} regulator\_demand_{area}}{\sum_{area} regulator\_demand_{area}} \qquad \text{EQ (3)}$$

B. Calculate the adaptive factor:

$$\alpha = \frac{market\_share_{ANSP}}{max\_market\_share} + \frac{E(demand_{ANSP})}{max\_demand_{ANSP}} \in [0,2] \qquad \text{EQ (4)}$$

With max_market_share the maximum allowed market share, $market\_share_{ANSP}$ the market share of the ANSP calculated in the previous step, $E(demand_{ANSP})$ the expected demand for the zones currently managed by the ANSP, and max_demand_{ANSP} the maximum demand the ANSP can control with the current resources.

C. **Calculate the minimum profitability:**

$$min\_profitability = min\_value + \alpha * \frac{max\_value - min\_value}{2}$$ EQ (5)

b) Calculate the probability of winning the auction based on the bid factor.

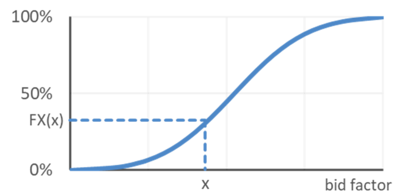
To calculate the probability of winning the auction, ANSPs use past data from their competitors. In the first phases of the simulation (until each area has been auctioned twice), as past data is not available, the ANSPs will bid the charge that ensures their minimum profit. Depending on their "bidding strategy" (each ANSP will be assigned only one bidding strategy, but different bidding strategies can exist within the same simulation), the learning method to calculate the probability of winning the auction will vary. Three different bidding strategies have been modelled:

A. **Friedman**

The ANSPs with this bidding strategy use historical bid data and characterise a competitor's bidding behaviour with a probability distribution which is a function of the bid factor.

If competitor *i* has enough bids, an empirical probability distribution function *FX(x)* of its bid factor may be constructed. With this distribution function, it is possible to calculate the probability P_i of beating competitor *i* with a given bid factor *x*.

$$P_i(x) = \Pr(X > x) = 1 - FX(x)$$ EQ (6)



The resulting probability of beating competitor *i* with a given factor is then adjusted to a sigmoid function as illustrated in Figure 6. The objective of adjusting the probability obtained to a sigmoid function is to avoid the existence of steps in the probability function.

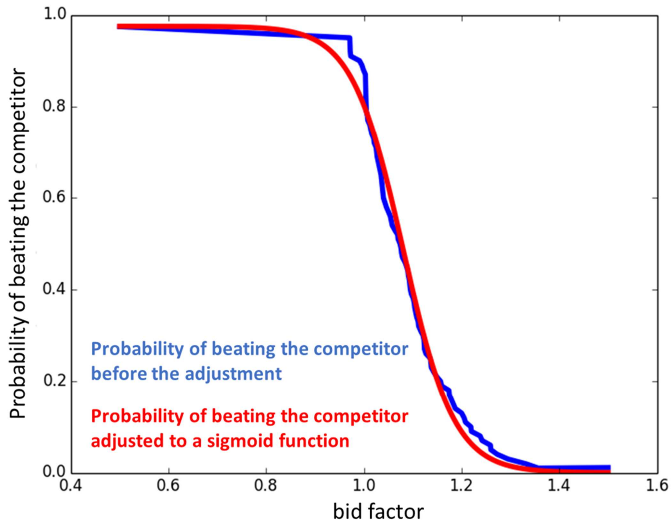


FIGURE 6 – PROBABILITY OF BEATING COMPETITOR *I*

Friedman [10] assumes that the bid factors of competitors are independent of each other. Therefore, the probability of winning the auction with a given bid factor, *x*, which means beating all competitors, can be determined as:

$$P(x) = \prod P_i\,(x) \quad i\ \epsilon\ competitors \qquad \text{EQ (7)}$$

B. Gates

This model calculates the probability of beating a single competitor exactly in the same way Friedman does, but differs in the way of obtaining the probability of winning the auction as it does not assume that the bid factors of competitors are independent from each other. Based on his experience as a principal estimator, Gates [11] developed the following equation for determining the probability of winning the auction with a given bid factor, *x.*

$$P(x) = \frac{1}{1 + \sum \frac{1 - P_i(x)}{P_i(x)}} \quad i\ \epsilon\ competitor \qquad \text{EQ (8)}$$

C. Fine

The main assumption of this model is that the only competitor the ANSPs are interested in beating is the lowest bid competitor [12]. Therefore, this model is based on collecting only the historical data of the lowest bid (i.e., the winner's bid) in each auction and, as in Friedman and Gates Models, calculates the probability of beating the "lowest competitor", what is equivalent to winning the auction.

$$P\ (x) = \Pr(X > x) = 1 - FX(x) \qquad \text{EQ (9)}$$

Quantitative methods	Friedman	Gates	Fine
Data	Uses historical bid data to characterise a competitor bidding behaviour		Uses only historical data of the winner of each auction
Bid factor function	FX(x): Distribution function of the bid factor of competitor i.		FX(x): Distribution function of the winner bid factor.
Probability of beating comp i	$Pi\ (x) = \Pr(X > x) = 1 - FX(x)$		Not Applicable
Probability of winning	$P(x) = \Pi Pi(x)$	$P(x) = \frac{1}{1 + \sum \frac{1 - P_i(x)}{P_i(x)}}$	$P\ (x) = \Pr(X > x) = 1 - FX(x)$

TABLE 1 – SUMMARY OF THE THREE BIDDING STRATEGIES

ANSPs estimate in an iterative process the best bid charge by multiplying the current charge by a bid factor, ranging from 0.5 to 1.5 in steps of 0.001. For each bid factor, they take the following actions (sections c) to g)).

c) Estimate the resources needed to manage the demand during the license period.

The ANSPs estimate the resources needed according to their productivity and the expected number of flights, calculated based on the passenger demand forecast and the average plane size and load factor. The productivity of ANSPs is a function of their technology level and the number of ATCOs. Depending on the resources required and the current resources, ANSPs may decide to hire or dismiss ATCOs.

d) Calculate the expected cost of the combination of areas that it is already controlling and the auctioned area during the license period.

Each ANSP calculates the expected costs of controlling the combination formed by the areas it is already controlling and the auctioned area as follows:

$$E(staff_{adjust}) = E(hiring_{ATCOs}) \times hiring\_cost\ + E(dismissed_{ATCOs})\ \times dismissal\_cost \qquad \text{EQ (10)}$$

$$E(Cost) = E(staff_{adjust}) + \sum_{area} E(staff_{cost_{area}}) \times indirect\_costs_{area} + fixed\_cost_{area} \qquad \text{EQ (11)}$$

e) **Calculate the expected income of the combination of areas that it is already controlling and the auctioned area during the license period.**

Each ANSP calculates the total expected income of the combination formed by the areas it is already controlling and the auctioned area as follows:

$$E(income) = \sum_{\substack{area \in \\ combination}} charge_{area} \times E(demand_{area}) \qquad \text{EQ (12)}$$

f) **Determine the expected profit during the license period.**

Each ANSP calculates the total expected profit of the combination formed by the areas it is already controlling and the auctioned area as follows:

$$E(profit) = E(income) - E(cost) \qquad \text{EQ (13)}$$

If the expected profitability is lower than the minimum profitability required by the ANSP (profitability = E(profit) / E(cost)) or the profit of the ANSP without controlling the area is greater than the profit after controlling that area, the ANSP rejects the option of bidding for the area with the bid factor under consideration.

g) **Determine the expected auction profit during the license period.**

The expected auction profit is calculated by multiplying the expected profit by the probability of winning the auction with the given bid factor:

$$E(auction\_profit) = probability\_winning \times E(profit) \qquad \text{EQ (14)}$$

After this iterative process, the ANSP selects the bid factor that maximises the expected auction profit and creates the bid which will be sent to the Regulator.

IV. Regulator: collect the bids and select the winner of the auction

After collecting the bids from all ANSPs, the Regulator allocates the auctioned area to the ANSP with the lowest bid factor. In the case of a tie, which occurs hardly ever, the area is allocated randomly (other rules could be possible, e.g. allocating the area to the ANSP with the lowest market share). The winning ANSP will manage the area during the following license period and the maximum charge applicable in the area will be the charge bid.

V. ANSPs: update their current working zones and calculate the investment

Once the Regulator has allocated the areas to the winning ANSPs, they update their charging zones and calculate the amount of capital to invest during the following license period in order to upgrade their technology level. This amount corresponds to a percentage (set to 80% in the experiments included in this deliverable) of the expected profit of the starting license period, regardless of the characteristics and size of the controlled areas

3.1.5.2.2 Evolutive process

In the evolutive process all the three agents participate. The sequence of agents' decisions and actions follows the scheme included in Annex I. Tendering simulation scheme - Figure 37, which is schematised in Figure 7.

The Regulator ensures that the ANSPs provide the required capacity and do not select a charge greater than the one they bid, and stores the public information that will be used by the ANSPs and the airline in future steps.

Similarly to the auctioning process, each ANSP takes the following actions for different combination of charges within the areas it is controlling: (i) estimate the resources needed according to the demand forecast, the charge of their competitors and the distance that each routes flies over each charging zone; (ii) estimate the profit of the combination of areas they control during the following time step; (iii) select the combination of charges that maximises their expected profit; and (iv) after each season, once the airlines have selected the route of the flights, update their economic results.

The airlines' objective is to meet the passenger demand minimising their costs. To do so, once the ANSPs publish the charge in each charging zone and according to the total passenger demand (which is assumed not to be affected by the charges), the airlines set the number of flights per OD pair and select the route of each flight according to a multinomial logit model [20] in which the costs of flying each route are the input data. The reason for using a logit model instead of choosing the cheapest route directly is that the model does not capture some elements such as congestion or weather conditions which can lead airlines to choose routes different form the ones that minimise the cost of fuel and air navigation charges.

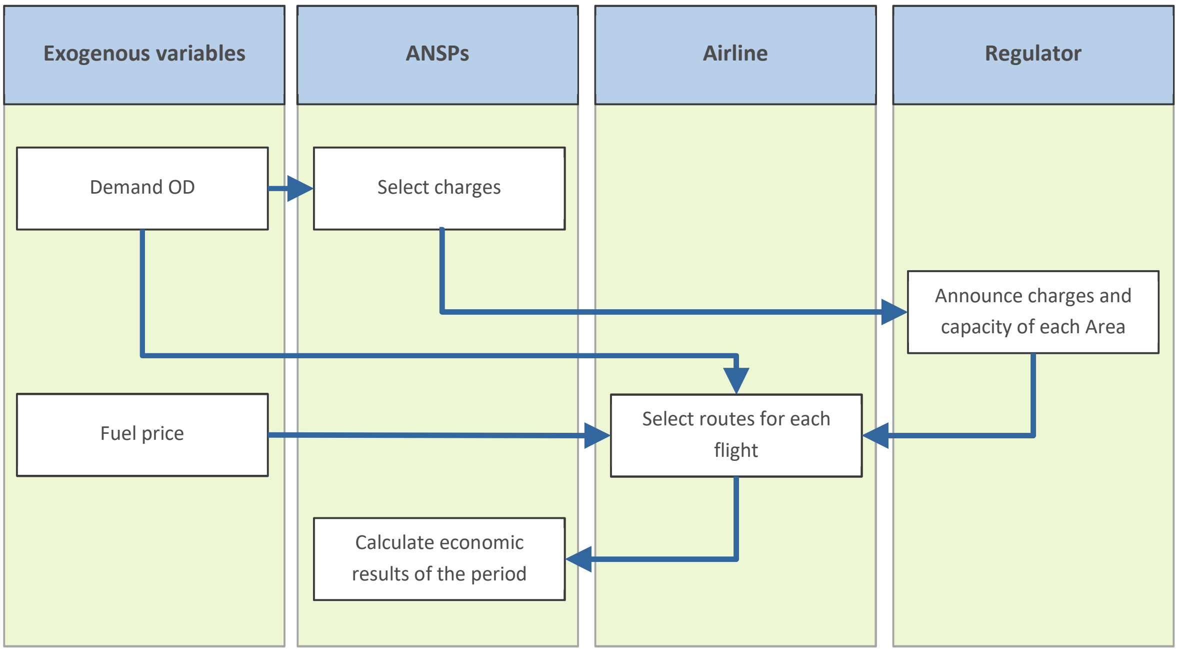


FIGURE 7 – SCHEME OF AGENTS' DECISIONS

I. ANSPs: select charge for the period

ANSPs select the charge of each area for the following period. Their objective is to maximise the expected profit. To select the charge, which cannot be higher than the cap-charge (i.e., the charge

ANSP submitted when winning the auction), they estimate the demand per area (flight-km) depending on the charge.

In order to get the charges that maximise their profit, ANSPs follow an iterative process for different values of the charges:

a) Estimate the demand.

To estimate the demand, ANSPs use the demand forecast and historical data about the charges of other ANSPs to simulate the airlines behaviour when selecting the routes.

b) Estimate the resources needed to manage the demand.

ANSPs estimate the resources needed based on the expected demand in the following time step, the real demand in the previous time step and the maximum productivity they can achieve. They may hire or dismiss ATCOs. In order to avoid a continuous process of hiring-dismissing ATCOs in the areas where seasonality has an important effect, the whole year is analysed.

c) Calculate the expected cost.

ANSPs calculate the costs of providing ATC services as follows:

$$E(staff_{adjust}) = E(hiring_{ATCOs}) \times hiring\_cost \ + E(dismissed_{atcos}) \ \times dismissal\_cost \qquad \text{EQ (15)}$$

$$E(cost) = E(staff_{adjust}) + \sum_{\substack{area \in \\ ANSP_{areas}}} E(staff_{cost_{area}}) \times indirect_{costs_{area}} + fixed_{cost}) \qquad \text{EQ (16)}$$

d) Calculate the expected income.

ANSPs calculate the total expected income of controlling their areas:

$$E(income) = \sum_{\substack{area \in \\ ANSP_{areas}}} charge_{area} \times E(demand_{area}) \qquad \text{EQ (17)}$$

e) Determine the expected profit.

ANSPs calculate the total expected profit of the combination:

$$E(profit) = E(income) - E(cost) - Investment \qquad \text{EQ (18)}$$

After this iterative process, the ANSPs establish the charges for each charging zone that maximise their total expected profit and adjust their staff accordingly.

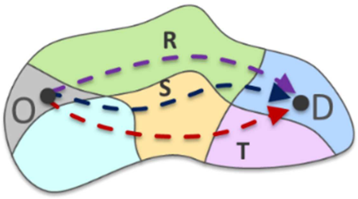
II. Regulator: collect the charges of each area and the capacity of each ANSP.

The Regulator collects the information from all the areas and communicates it to the Airlines.

III. Airlines: select the route of each flight.

The airlines calculate the utility of each route of the OD pair as the inverse of the cost of flying the route. The cost of flying each route is calculated using their operating costs, the fuel cost and the charges of each charging zone. Then, they select the route for each flight using a multinomial logit model (MNL) [20], which uses the utility of flying each route as the input data.

$$cost_S = cost_{S,fuel} + cost_{S,charges} + cost_{S,op}$$
$$cost_{S,fuel} = CASK_{fuel} \times l_S \times a_c$$
$$cost_{S,op} = CASK_{other} \times l_S \times a_c$$
$$cost_{S,charges} = \sum_a l_{s,a} \times charge_a$$



with:

l_S: length of route s $l_{s,a}$: length of route s in airspace a

a_c: aircraft capacity $charge_a$: charge in airspace a EQ (19)

$CASK_{fuel}$ = cost of fuel per available seat kilometre

$CASK_{other}$ = cost of per available seat kilometre excluding fees and fuel

$$P(r = S) = \frac{e^{utility(S)}}{\sum_r e^{utility(r)}}, \qquad K_{OD} = max(cost_r)$$

with r running over all possible routes for a given pair,

$$Utility_R = K_{OD}/cost_R$$

IV. ANSPs. Calculate the economic result of the period

Once the Airlines select the routes of each flight, the ANSPs obtain the actual demand in each area and calculate their actual profit in order to update their capital.

3.1.6 Exogenous variables

Exogenous variables are used to establish arbitrary external conditions that affect the model but are not affected by it. The main exogenous variables considered in the model are the fuel price and the passenger demand. Both variables are modelled as random variables. The purpose of including exogenous variables with a stochastic component is to test the ability of the different agents to adapt to changing circumstances in the presence of uncertainty.

Exogenous variables include:

- Passenger demand: it defines a number of passengers at each simulation step and for each origin-destination pair. Forecasted passenger demand is known by all the agents. The Regulator uses it to establish the minimum capacity the ANSPs have to provide in each charging zone. ANSPs employ it in order to establish the unit charge for each time step. Finally, Airlines require this information to set the number of flights per origin-destination pair.
- Fuel price: it defines the cost of fuel per available-seat-km.
- ATM technology gains: it controls the efficiency gains that can be obtained by ANSPs by investing in new technologies. To set these values, the Master Plan 2012 data have been employed.
- ATCOs' cost: it defines the cost of a working hour of a new ATCO.

Different scenarios can be defined by combining these variables (e.g., low fuel price, high demand, slow ATM technological evolution).

Actual values for the exogenous variables are calculated by the model as a deviation from the forecasted data, by adding a stochastic noise at each simulation step. As a result, actual values may differ from the forecast, and the forecasted values for the following simulation steps are modified accordingly.

To account for the uncertainty in the evolution of these variables, three values are generated:

- Scenario Value SV(t), defined as an input to the simulation as part of the scenario configuration.
- Forecast value FV(t), re-calculated at each time step:

$$FV(t+i) = SV(t+i) + [AV(t-1) - SV(t-1)] \ \forall\, i \geq 0 \qquad \text{EQ (20)}$$

- Actual value AV(t) generated by using a normal distribution of probability centred in the FV(t), with standard deviation controlled by a volatility factor VF:

$$P\big(AV(t) \in \big[[(1-VF) \times FV(t), (1+VF) \times FV(t)]\big]\big) = 0.997 \qquad \text{EQ (21)}$$

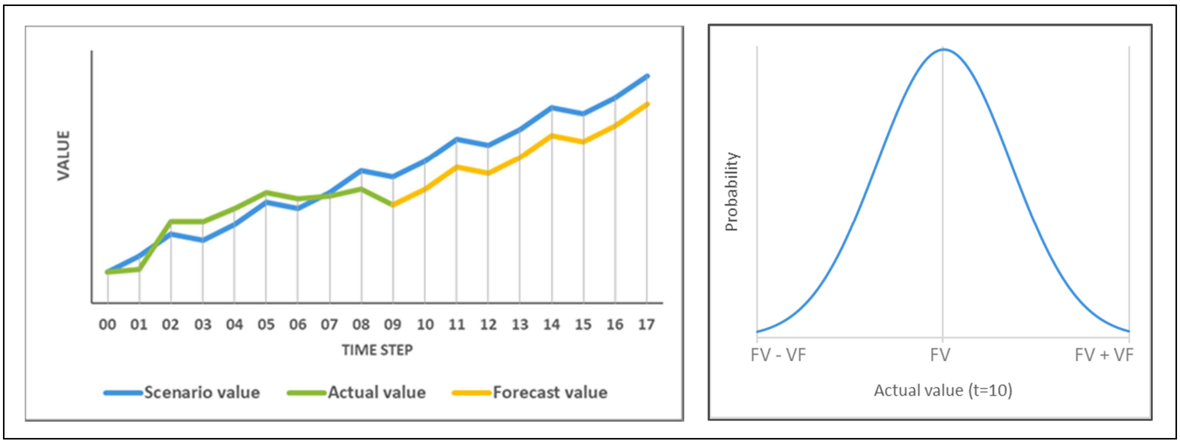


FIGURE 8 – EXAMPLE OF SCENARIO, ACTUAL AND FORECAST VALUE AT TIME STEP 9

3.2 Simulation scenarios

The proposed case study simulates the hypothetical outcome of the liberalisation of the ATM market in Western Europe until 2050, if liberalised in 2015, according to different auctioning parameters. The model has been initialised with the ANSPs' and airlines' data of 2014 year ended, summarised in Table 2 and Table 3.

3.2.1 General parameters

3.2.1.1 Geographic context

The network analysed is presented in Figure 9 and Figure 10. It includes eleven charging zones (one charging zone per country), eleven ANSPs (an ANSP per charging zone) and a set of possible routes between the thirteen airports considered in the simulation. The thirteen airports considered are: Lisbon, Madrid, Dublin, Edinburgh, London, Paris, Amsterdam, Brussels, Frankfurt, Berlin, Copenhagen, Milan and Rome. Generally, the main airport of each country has been selected. In the cases of UK and Germany, as London and Frankfurt are close to the frontier, Edinburgh and Berlin were also considered.

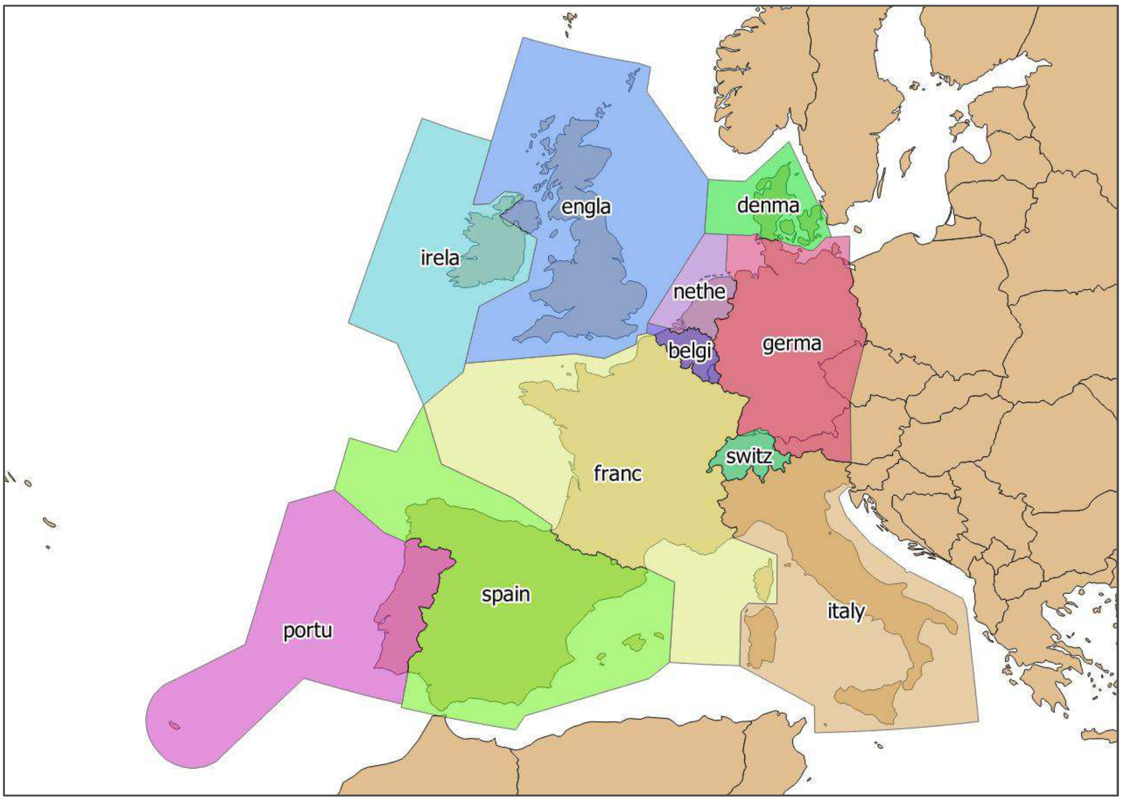


FIGURE 9 – COUNTRIES ANALYSED IN THE CASE STUDIES

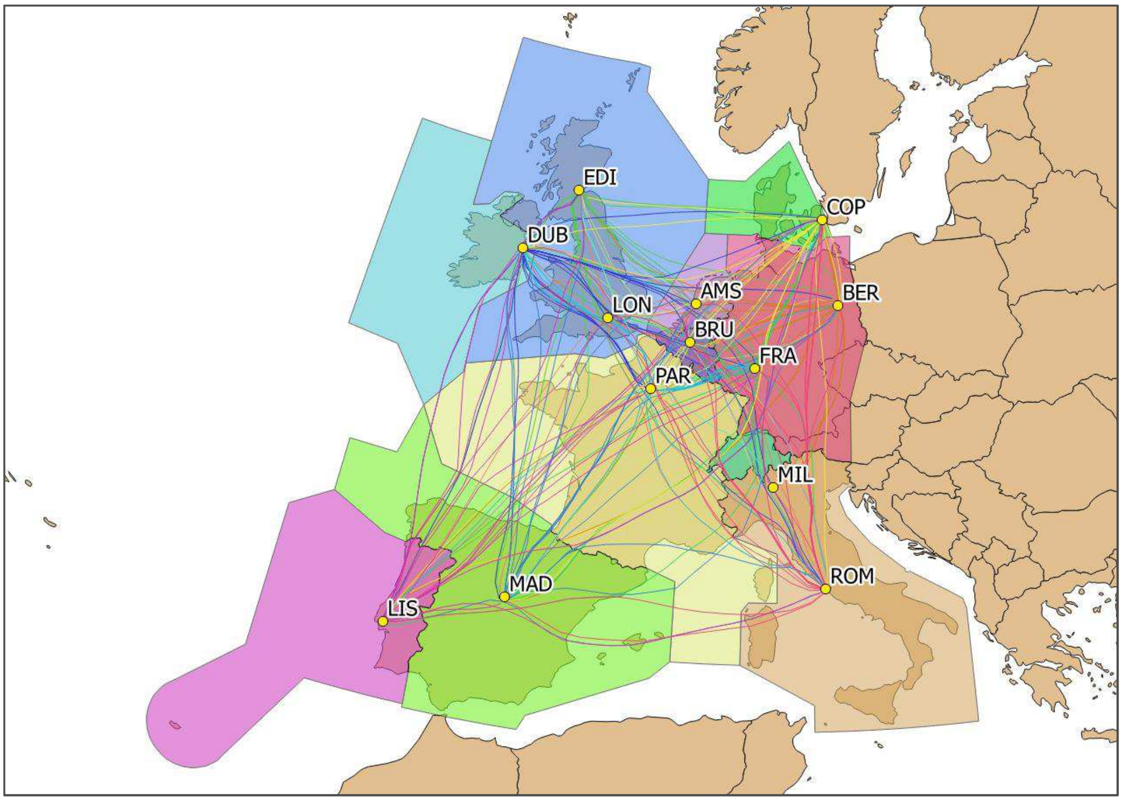


FIGURE 10 – SET OF AIRPORTS AND ROUTES IN THE CASES OF STUDY

3.2.1.2 ANSP and airline data

The ANSP data have been obtained from the ATM Cost-Effectiveness Benchmarking Report from 2014 [18]. These data have also been employed to calibrate the number of flights per OD pair since the network is a simplification of reality (e.g., the number of airports is reduced and there are no flights coming from outside the case study) and the number of flights has to be adapted to this network. Given the distribution of flights per OD pair, and the distance that each route flies over the charging zones, the number of flights per OD pair has been adjusted to obtain the actual demand of 2014 in every country.

The ANSPs we have simulated are Belgocontrol (Belgium), DFS (Germany), DSNA (France), ENAIRE (Spain), ENAV (Italy), IAA (Ireland), LVNL (Netherland), NATS (United Kingdom), NAV (Portugal), NAVIAIR (Denmark) and Skyguide (Switzerland), which represent 60.5% of the total IFR flight-km in Europe. The figures of the Maastricht Upper Airspace Control Centre (MUAC), which is in charge of the upper airspace in Belgium, Netherlands and Northwest Germany have been split into these countries. The data of these ANSPs are summarised in Table 2. The hourly cost of new ATCOs in the simulation has been set equal to the lowest ATCO cost of the analysed ANSPs, the dismissal cost of an ATCO to the cost of an ATCO working six months and the hiring cost of an ATCO to the cost of an ATCO working three months. The range of the minimum required profitability has been set to 5-10%, taking into account that the profitability of 20 out of 36 ANSPs in the ATM Cost-Effectiveness Benchmarking Report from 2014 lies within this interval.

ANSP	Staff cost	Non-staff operating cost	Other cost	IFR flight-km controlled	Average charge per km
Belgocontrol	98,878	15,125	20,724	173,363,055	0.96
DFS	629,674	81,089	185,788	1,103,672,532	0.73
DSNA	641,889	190,011	127,025	1,542,050,584	0.78
ENAIRE	393,806	67,896	142,563	882,223,857	0.79
ENAV	295,596	113,719	146,563	711,039,027	0.83
IAA	52,933	20,728	14,857	214,828,496	0.55
LVNL	126,826	22,445	11,286	209,564,804	0.58
NATS	319,672	87,237	188,703	798,501,566	0.98
NAV	72,724	8,721	7,964	240,379,955	0.49
NAVIAIR	48,617	12,169	19,338	138,344,091	0.66
Skyguide	141,141	13,848	33,792	208,425,913	0.70

TABLE 2 – ANSP DATA (FROM ACE REPORTS)

The data used to model the airline agent have been obtained from the annual financial reports of the main European airlines ([14], [15], [16] and [17]) and are presented in Table 3. As seen in Table 3, the cost per available seat-kilometre (CASK) differs considerably between airlines. In the present case study, the cost of fuel per available seat-kilometre (CASK fuel) has been set to 2.05 €cent and the cost per available seat-kilometre excluding fees and fuel (CASK other) has been set to 4.5 €cent.

Airline	CASK (€ cent)	CASK fees (€ cent)	CASK fuel (€ cent)	CASK other (€ cent)
EasyJet	5.91	0.46	1.87	3.58
Air France	6.93	0.53	1.90	4.50
Lufthansa	8.8	1.47	1.89	5.44
British Airways	7.49	0.55	2.45	4.49
Average Airline	**Output of the model**	**Output of the model**	**2.05**	**4.50**

TABLE 3 – CASK DATA

3.2.1.3 Temporal scope and time step

The temporal scope of the case studies is set to 2050, as specified in COMPAIR deliverable D2.2 [18]. In order to analyse the possible effects of seasonality, such as economies of scale in the case of controlling complementary charging zones (those in which the workload is seasonal and does not coincide in time), the time step is set to six months. Every six months, ANSPs are allowed to change their unit charge in each country (according to the forecast demand and the past data of their competitors and the airlines' choices) and adjust their resources (number of ATCOs).

3.2.1.4 Demand forecast

The demand forecast has been obtained from EUROCONTROL's report "Challenges of Growth 2013. Task 7" [19]. According to it, there exists a great uncertainty between scenarios, with the total demand in the most optimistic scenario being almost three times the demand of the less optimistic scenario, as depicted in Table 4. We have employed the data of the most likely scenario, the so-called "Regulated growth", which considers that the demand will grow 1.8% annually. According to this scenario, the demand in 2050 will be twice the current demand.

Scenario	2012-2035	2035-2050
Global growth	2.6%	2.8%
Regulated growth	1.8%	1.8%
Fragmenting world	0.7%	-0.4%

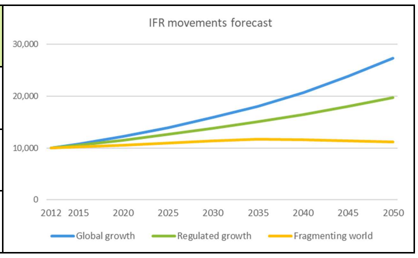


TABLE 4 – SUMMARY OF SCENARIO FORECASTS ANNUAL GROWTH (FROM [19])

3.2.1.5 Auctioning schedule

In the scenarios analysed, all the charging zones are auctioned within the same time-step. The first auction takes place on the second time-step. Then, the frequency of auctions depends on the licenses duration of the specific scenario.

3.2.2 Objectives of the simulation scenarios

As the objective of the model is to analyse the outcome of different ANSPs' and auction's parameters, we have modelled several scenarios by modifying the main parameters of the auctioning process.

3.2.2.1 ANSP parameters

ANSPs have different bidding strategies (i.e., learning methods) to create the optimal bids. In this analysis, we will discuss the outcome of each bidding strategy and which one is the dominant, if any.

3.2.2.2 Auction parameters

To analyse the outcome of different auction parameters, different scenarios are built by modifying the main parameters of the auctioning process: the maximum allowed market share, the auctioning order, and the duration of the licenses.

3.2.2.2.1 Market share

The goal of establishing a maximum market share, calculated as the flight-km controlled by an ANSP divided by the total flight-km in the network, is to avoid the appearance of monopolistic or oligopolistic behaviours, as it ensures the existence of a minimum number of ANSPs.

We will analyse the outcome with three different values for the maximum market share: 30%, 40% and 60%, which will ensure the existence of at least 4, 3 and 2 ANSPs in each scenario, respectively.

3.2.2.2.2 Auctioning order

In the simulation, the charging zones are auctioned individually and, when auctioned in the same step, sequentially. Thus, the order in which they are auctioned is important (e.g., due to the maximum allowed market share, it may occur that an ANSP cannot bid for some area depending on the areas allocated to that ANSP in previous auctions).

We will analyse the outcome of auctioning the areas in different orders, according to the market share of the countries: ascending, descending and mixed order. When the order is set to mixed, first the zone with the lowest market share will be auctioned, followed by the zone with the greatest market share, then the zone with the second lowest market share, and so on.

- ASCENDING ORDER: Denmark, Belgium, Switzerland, Netherlands, Ireland, Portugal, Italy, United Kingdom, Spain, Germany, France
- DESCENDING ORDER: France, Germany, Spain, United Kingdom, Italy, Portugal, Ireland, Netherland, Switzerland, Belgium, Denmark
- MIXED ORDER: Denmark, France, Belgium, Germany, Switzerland, Spain, Netherlands, United Kingdom, Ireland, Italy, Portugal

3.2.2.2.3 License duration

The license duration determines the frequency of auctions. The longer the license duration, the fewest auctions will take place within the simulation. If only few auctions occur, ANSPs do not have enough data to properly analyse the bidding behaviour of their competitors. However, the total profit of the licenses is expected to be greater as the duration of licenses increases and ANSPs secure their income for a larger period of time, which could favour the investment on technology.

Two different values of the licenses duration will be analysed: 5 and 10 years. Longer periods could lead to ANSPs investing more money since they will have more time to recover the investment. On the contrary, shorter periods could favour the competition between ANSPs and incentivise the investment since more tendering process would take place.

3.3 Analysis of results

3.3.1 ANSP parameters

The main attribute of ANSPs that affects their performance during the auctioning is the learning method from their competitors' bids. In order to analyse the outcome of each strategy, different simulations have been run. To compare the effectiveness of the bidding strategies on the outcome of the tendering, the initial productivity of ANSPs is equal to 1 (an ATCO can monitor a flight) and the investment in technology by the ANSPs is set to zero, so the technology level of ANSPs is kept constant throughout the simulation. For this analysis, no volatility in passenger demand is considered.

The scenario parameters are:

Parameter	Value
License duration	5 years
Maximum market share	60%
1st auction (all charging zones)	6 months from the beginning (June 2015)
Auctioning order	Ascending (from smallest to biggest charging zone)

TABLE 5 – SCENARIO PARAMETERS TO ANALYSE THE IMPORTANCE OF THE BIDDING STRATEGY

Several simulations were conducted to analyse the bidding strategy parameter. The bidding strategy of ANSPs in these simulations was varied in order to analyse the differences produced by this parameter regardless of the ANSPs' initial status. The results of all the simulations were rather similar. In this section, we present the results of a specific simulation in which the ANSPs have been modelled according to the following bidding strategy:

ANSP	Strat
ANSP00	Gates
ANSP01	Fine
ANSP02	Friedman
ANSP03	Gates

ANSP	Strat
ANSP04	Fine
ANSP05	Friedman
ANSP06	Gates
ANSP07	Fine

ANSP	Strat
ANSP08	Friedman
ANSP09	Gates
ANSP10	Fine

TABLE 6 – ANSPS' BIDDING STRATEGY

10 simulations have been executed according to these parameters and the average results obtained are shown in Table 7. The values of Friedman represent the sum of the outcomes of ANSP02, ANSP05 and ANSP08; the values of Gates represent the sum of the results of ANSP00, ANSP03, ANSP06 and ANSP09; and the values of Fine represents the sum of the results of ANSP01, ANSP04, ANSP07 and ANSP10. As the learning method is not used until the 3rd auction (2025), only the data from 2025 to 2050 are analysed.

ANSPs' bidding strategy	Total Profit 2025-2050 (M€)	Total Demand 2025-2050 (M km)	Average Market share 2025-2050 (%)	Average Unit profit 2025-2050 (cents€)
Friedman	1,765	293,414	53%	0.60
Gates	2,144	218,965	40%	0.98
Fine	357	47,741	7%	0.84

TABLE 7 – RESULTS 2025 - 2050

These results suggest that the ANSPs employing the Friedman model behave more aggressively offering lower charges, so their market share is higher, but they obtain lower unit profit than their competitors. It is noticeable that, even though the market share of Friedman was 30% larger than the Gates' market share, its total profit was 30% lower than Gates' profit.

The results of the period could suggest that there is competition between ANSPs regardless their bidding strategy. Nevertheless, the evolution of the market share (Figure 11) shows that in the long term the ANSPs using the Friedman strategy will control the entire market. In the first two auctions, the agents do not analyse the data of their competitors in past bids. In 2025, when agents begin to analyse these data, the agents which are modelled according to the Friedman model evolve to control a larger market share. Figure 11 shows that in 2050, 27% of agents (those which use the Friedman strategy) obtain a market share over 80% with a rising tendency.

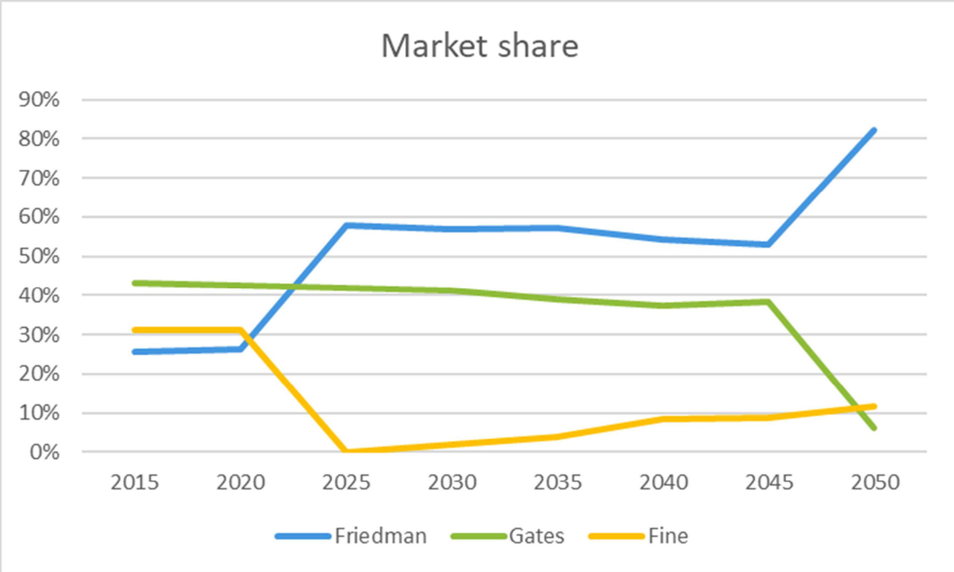


FIGURE 11 – EVOLUTION OF THE MARKET SHARE DEPENDING ON THE BIDDING STRATEGY

To understand the different outcomes obtained using the Friedman, Gates or Fine model, Figure 12 illustrates the probability of an ANSP (ANSP10 in this case) of beating their competitors individually and the probability of winning the auction according to Friedman's and Gates' strategy in the sixth auctioning process of the simulation. The model shows clearly that, as the bid factor increases, the probability of winning the auction decreases more rapidly in the Friedman model than in the Gates model, so the ANSPs modelled to employ the Friedman model, tend to submit lower bids.

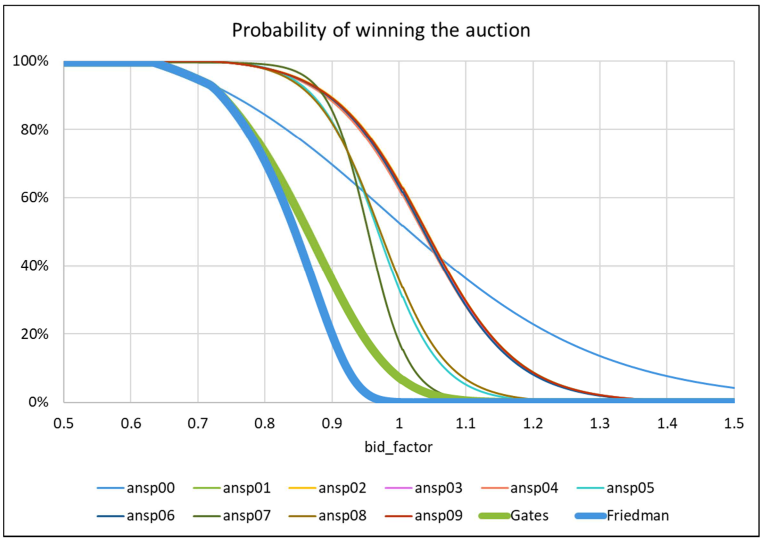


FIGURE 12 – PROBABILITY OF ANSP10 OF BEATING THE COMPETITORS AND WINNING THE AUCTION ACCORDING TO FRIEDMAN AND GATES MODELS

3.3.2 Auctioning parameters

In the previous section, it has been deduced that the bidding strategy of the ANSPs has an important effect on the outcome. Since the objective of this section is to analyse the outcome of different auctioning parameters, in the following scenarios all ANSPs employ the same bidding strategy so the difference in the outcome is derived from the auctioning parameters and not the ANSPs.

ANSPs' bidding strategy has been set to Gates as:

- In Friedman model, the probability of winning the auction decreases rapidly; in the previous case study, such probability has been observed to be close to 0 for values of the bid factor greater than 0.95. If all the ANSPs were modelled to use Friedman, the probability of winning the auction would decrease even more rapidly as all the ANSPs would behave more aggressively than in the previous case study, in which Gates and Fine ANSPs behave more conservatively.
- In the case of setting ANSPs' bidding strategy to Fine, they will obtain the same probability of winning the auction since the data employed would be the same for all the ANSPs. As one of the benefits of the ABM modelling is the possibility of modelling heterogeneous agents, it seems more interesting to use a learning method which characterises the ANSPs individually.
- The Gates model allows the ANSPs to characterise the behaviour of each single competitor and bid according to the ANSPs participating in the auction.

The parameters that we will analyse are:

Auctioning order	• **ASCENDING ORDER**: Denmark, Belgium, Switzerland, Netherlands, Ireland, Portugal, Italy, United Kingdom, Spain, Germany, France • **DESCENDING ORDER**: France, Germany, Spain, United Kingdom, Italy, Portugal, Ireland, Netherland, Switzerland, Belgium, Denmark • **MIX ORDER**: Denmark, France, Belgium, Germany, Switzerland, Spain, Netherlands, United Kingdom, Ireland, Italy, Portugal
Licenses duration	• **5 years** • **10 years**
Maximum market share	• **30%** • **40%** • **60%**

TABLE 8 – AUCTIONING PARAMETERS

3.3.2.1 Market share

Three different values of the maximum market share have been analysed: 30%, 40% and 60%. In these scenarios, the auctioning order is set to mixed order and the licenses duration to five years.

For a maximum market share of 30%, we find more market competition between ANSPs than with a maximum market share of 40% or 60% (Figure 13). In the 30% scenario, the market is shared by 4 ANSPs with a similar market share, between 20% and 30% (Figure 13.a). In the case of a maximum market share of 40%, two big ANSPs control almost 40% of the market each, and two or three ANSPs control minor areas (Figure 13.b). When the maximum market share is set to 60%, there is one dominant ANSP whose market share tends to increase in every tendering process, controlling more than 50% at the end of the period of study. Moreover, in this scenario the whole market is controlled by fewer, only three, ANSPs (Figure 13.c).

The maximum market share does not seem to affect the trend followed by the evolution of the average network charges (Figure 15) and the total number of ATCOs in the network (Figure 16), but it does affect the actual values obtained in 2050. In the case of a maximum market share of 40%, the average charge obtained in 2050 is 38 €cents/km, 10% greater than in the case of a maximum market share of 60%, and the total number of ATCOs is 15% greater. This is due to the investment in technology made by ANSPs. In the 60%-scenario, the total profit is divided by a fewer number of ANSPs, which have more capitaly to invest in technology and increase their efficiency/technology level to a greater extent than in the 30% or 40%-scenarios (Figure 17).

In spite of these advantages, a maximum market share of 60% could lead to an oligopoly in which the market is dominated by two ANSPs which control over 90% of the market, with a tendency to increase this percentage. The emergence of oligopolies is an undesired outcome of the liberalisation of any market. Thus, it may be concluded that a maximum market share over 50%, although presenting some minor benefits in the short-term period, could lead to a market failure in the long-term. When limiting the market share to 40%, four ANSPs out of eleven continue in the market, which seems more appropriate to ensure the competition between them and obtain more efficient ANSPs than in the 30%-scenario.

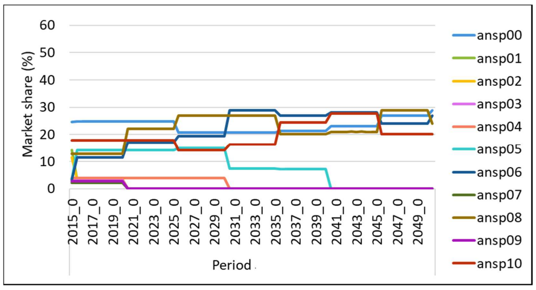


FIGURE 13.A 30%

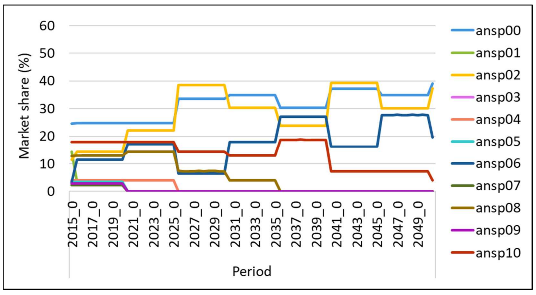


FIGURE 13.B 40%

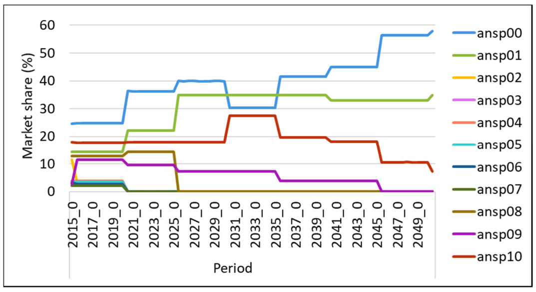


FIGURE 13.C 60%

FIGURE 13 – ANSPS' MARKET SHARE

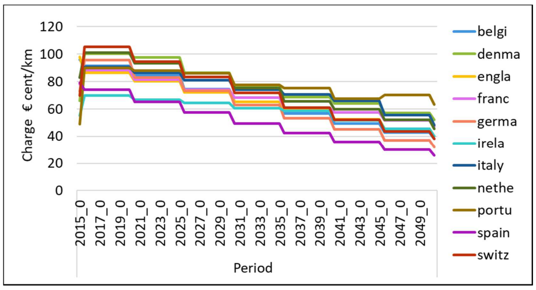


FIGURE 14.A 30%

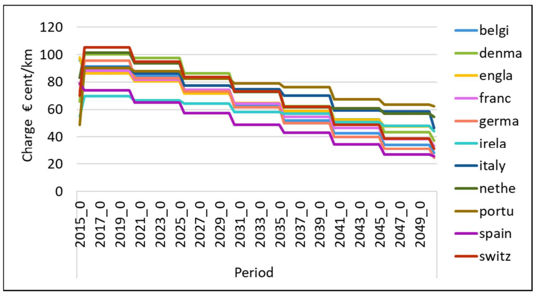


FIGURE 14.B 40%

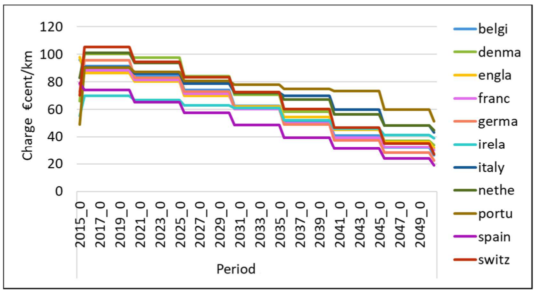


FIGURE 14.C 60%

FIGURE 14 – CHARGE PER COUNTRY

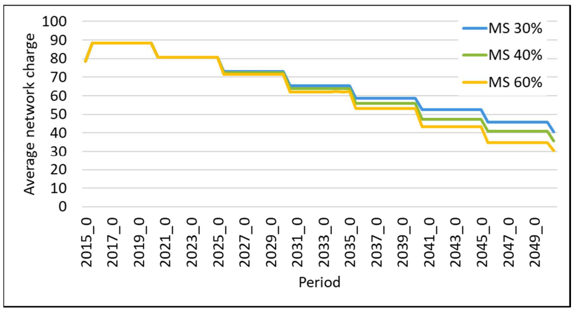


FIGURE 15 – AVERAGE NETWORK CHARGE

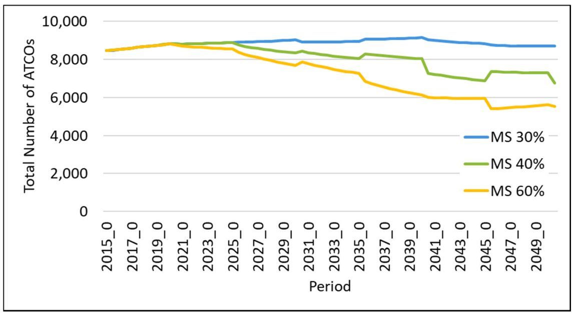


FIGURE 16 – TOTAL NUMBER OF ATCOS

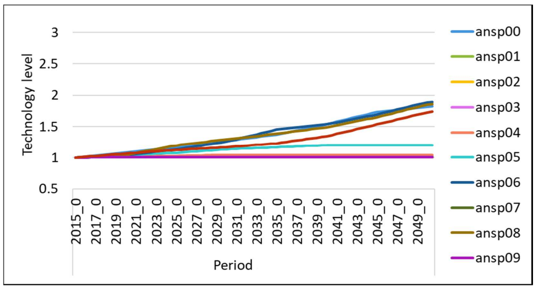


FIGURE 17.A MAXIMUM MARKET SHARE OF30%

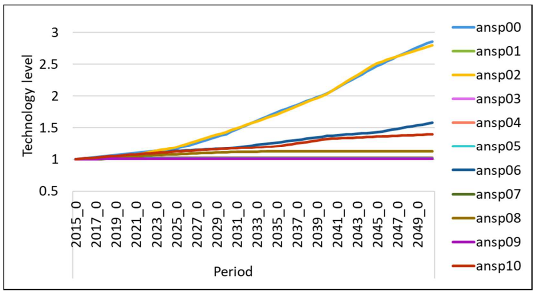


FIGURE 17.B MAXIMUM MARKET SHARE OF 40%

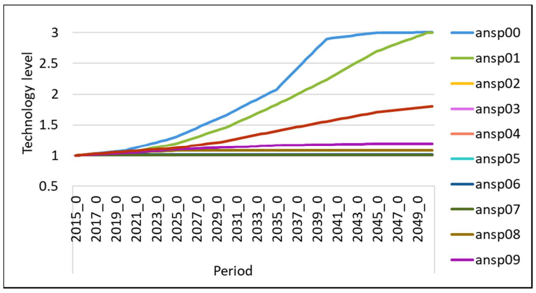


FIGURE 17.C MAXIMUM MARKET SHARE OF 60%

FIGURE 17 – ANSP'S TECHNOLOGY LEVEL

3.3.2.2 Auctioning order

In this section, the effect of the auctioning order on the tender outcome is evaluated. In this analysis, we consider three different scenarios in which the maximum market share is set to 40% and the licenses duration to 5 years.

We can conclude that the auctioning order influences locally the charging prices resulting from the tendering but has a minor impact on the global outcome.

Figure 18 presents the resulting charges obtained in each country for different auctioning orders in a scenario with a maximum market share of 40%. It may seem that, in the "descending" order (Figure 18.a), the total fees the airlines will have to pay are higher than in the other scenarios. However, the average network charge paid by the airlines is quite similar for the three auctioning orders considered (Figure 18.d). The reason is that in the "descending" scenario, the biggest countries are auctioned first and the ANSPs behave more aggressively, offering lower charges. Finally, when the smaller areas are auctioned, the dominant ANSPs have ensured a high market share for the following license period, perhaps close to the maximum market share, and they are not allowed to participate in the remaining tenders or they are not interested in getting the remaining areas unless they obtain a great profit. Then, the less efficient ANSPs (i.e., those whose technology level is lower) have a chance to be allocated one of the small countries, despite offering a higher charge. The same effect occurs with the latest zones to be auctioned in the "ascending" (Figure 18.b) and the "mixed" order (Figure 18.c) scenarios, but to a minor extent. In the three scenarios, it is observed that the last zone to be auctioned gets the highest charges (Denmark in the "descending" scenario, France in the "ascending" scenario, and Portugal in the "mixed" scenario), with differences in charges particularly noticeable in the "descending" one.

Comparing Figure 18.a, Figure 18.b and Figure 18.c, we can conclude that the mixed ascending produces more heterogeneous charges between the countries that are auctioned first (France, Germany and Spain) and the other countries, especially Denmark.

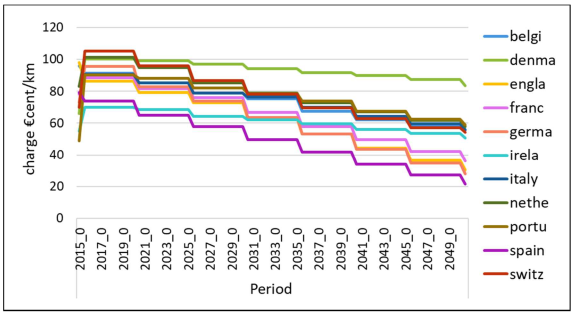


FIGURE 18.A AUCTIONING ORDER SET TO DESCENDING

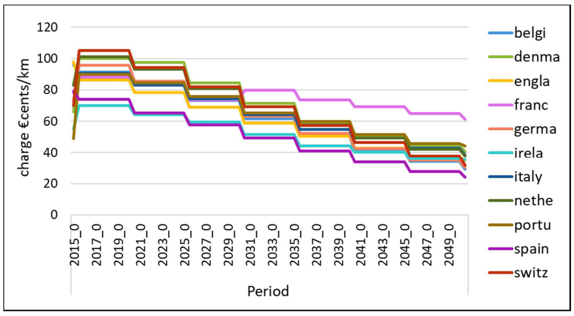


FIGURE 18.B AUCTIONING ORDER SET TO ASCENDING

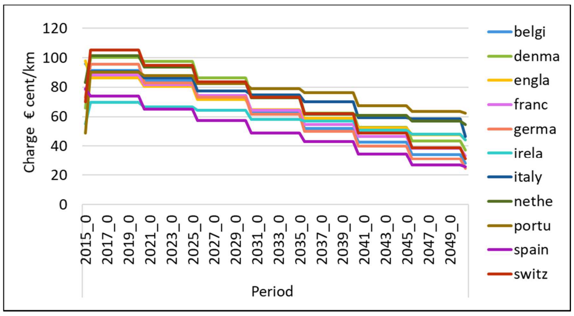


FIGURE 18.C AUCTIONING ORDER SET TO MIXED

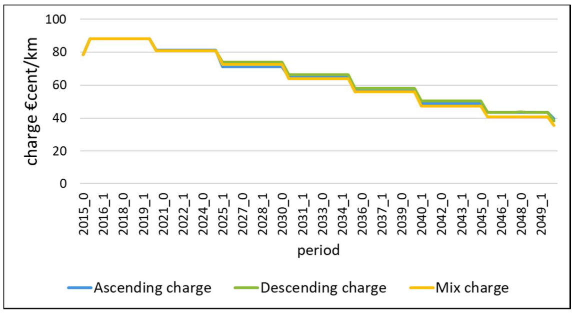


FIGURE 18.D AVERAGE MARKET CHARGE

FIGURE 18 – INFLUENCE OF THE AUCTIONING ORDER IN THE CHARGES FOR A MAXIMUM MARKET SHARE OF 40%

Figure 19, Figure 20 and Figure 21 present the total number of ATCOs, the total investment made by ANSPs and the technology level of ANSPs for the different auctioning orders. The total investment and the number of ATCOs are correlated: the higher the investment done by the ANSPs, the higher their productivity and the lower the number of ATCOs required, due to the improvement in efficiency obtained from the investment. It can also be observed that, when the order is set to "mixed", the investment made by the ANSPs increases and so does their efficiency, so the total number of required ATCOs in the network decreases.

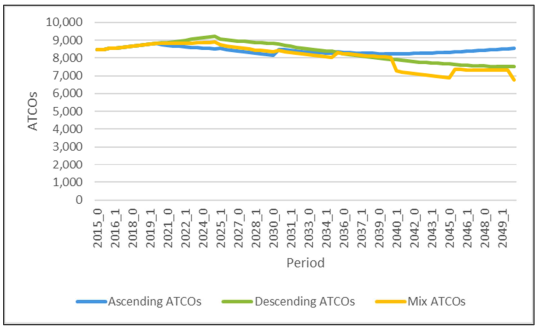


FIGURE 19 – TOTAL NUMBER OF ATCOS

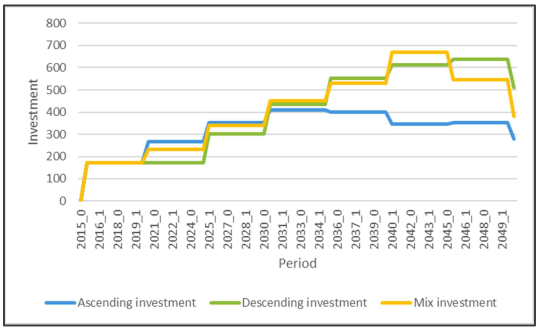


FIGURE 20 – TOTAL INVESTMENT

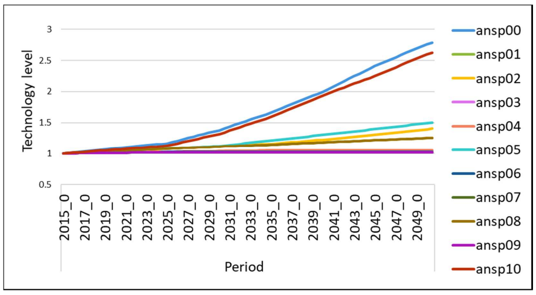


FIGURE 21.A AUCTIONING ORDER SET TO DESCENDING

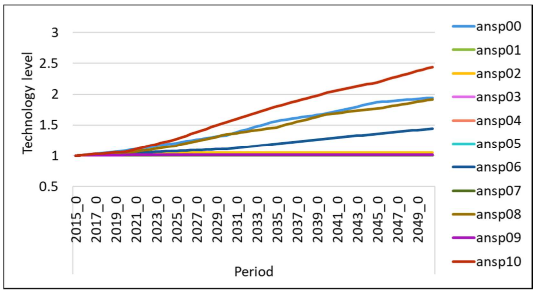


FIGURE 21.B AUCTIONING ORDER SET TO ASCENDING

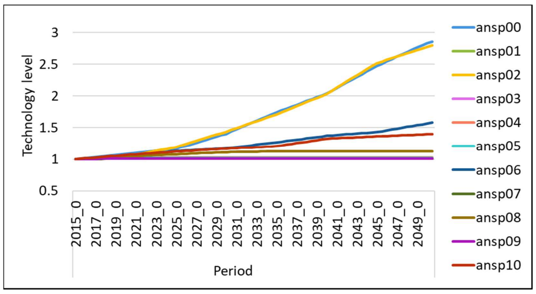


FIGURE 21.C AUCTIONING ORDER SET TO MIX

FIGURE 21 – ANSP'S TECHNOLOGY LEVEL FOR A MAXIMUM MARKET SHARE OF 40

3.3.2.3 License duration

The last parameter to be evaluated in this document is the frequency of auctions. Two scenarios have been evaluated: (i) a 5-year license duration; and (ii) a 10-year license duration. For both scenarios, the maximum allowed market share was set to 40% and the auctioning order to "mixed". The results are depicted in Figure 22 and Figure 23.

The charges in both scenarios tend to decrease at the same rate. Also, the rates in 2050 are almost the same for both scenarios (Figure 23). Since the charges fall at the same rate, the average bid factor of the winning bids lowers as the frequency of auctions decreases (Figure 24).

There is a considerable difference in the resulting market share of the ANSPs for the two scenarios. In the 10-year scenario (Figure 22.a) the outcome suggests that the market share of ANSPs remains quite stable from 2035 to 2050. Five ANSPs control the whole market, with 4 of them having a market share over 15%, indicating that the ANSPs are quite homogeneous. In the 5-year scenario, the ownership of the charging zones switches after every tendering process (Figure 22.b). Two dominant ANSPs control 40% of the market each, the maximum they are allowed to, and the remaining zones are shared by two minor ANSPs. It can be concluded that a license duration of 10 years leads to more homogeneous ANSPs and more stable market with more ANSPs, but not necessarily to a more competitive market. In the 5-year scenario the number of ATCOs is reduced faster (Figure 25) due to the faster uptake of new technology (Figure 26).

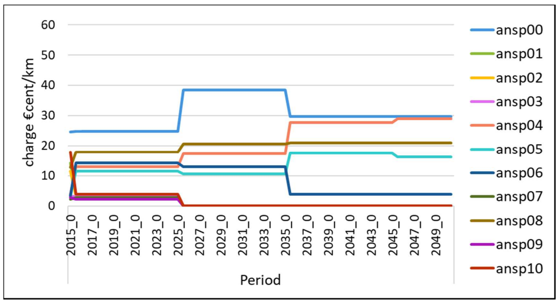


FIGURE 22.A LICENSE'S DURATION SET TO 10 YEARS

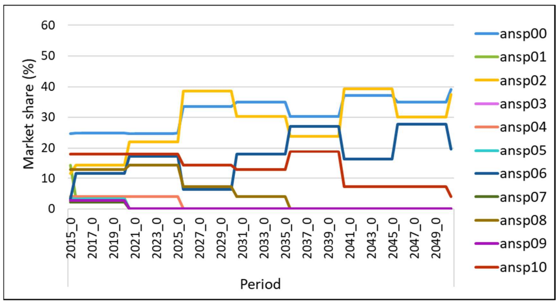


FIGURE 22.B) LICENSE'S DURATION SET TO 5 YEARS

FIGURE 22 – ANSPS' MARKET SHARE

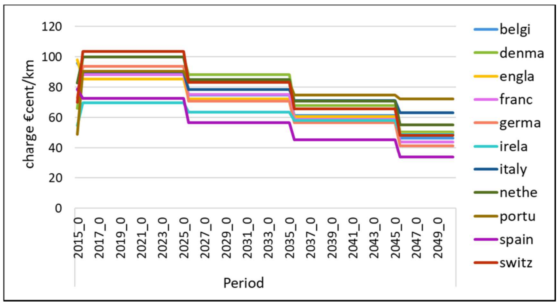


FIGURE 23.A LICENSE'S DURATION SET TO 10 YEARS

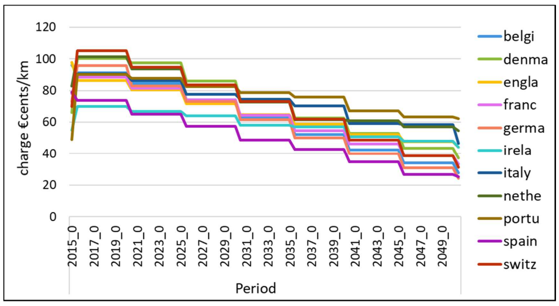


FIGURE 23.B) LICENSE'S DURATION SET TO 5 YEARS

FIGURE 23 – CHARGE PER COUNTRY

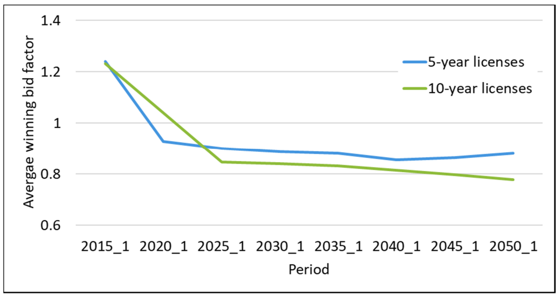


FIGURE 24 – AVERAGE BID FACTOR

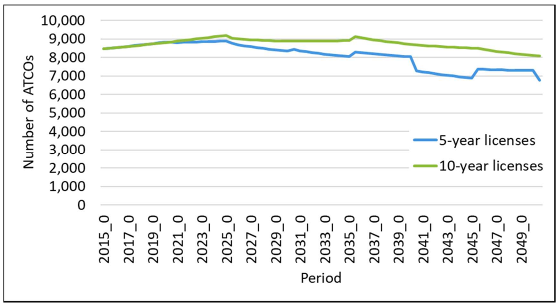


FIGURE 25 – TOTAL NUMBER OF ATCOS

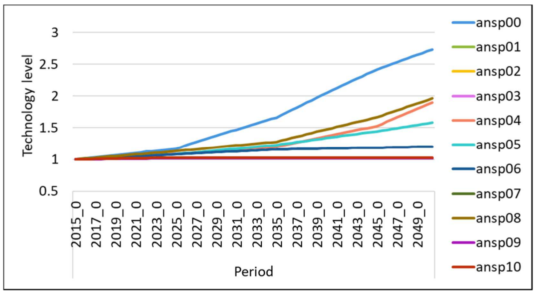


FIGURE 26. A LICENSE'S DURATION SET TO 10 YEARS

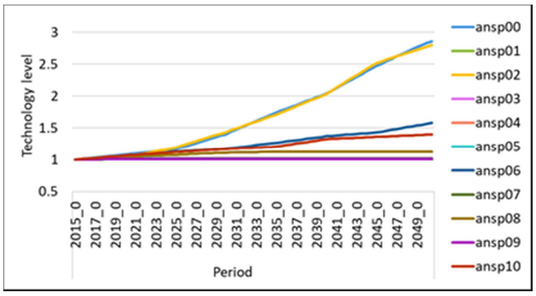


FIGURE 26. B LICENSE'S DURATION SET TO 5 YEARS

FIGURE 26 – ANSPS' TECHNOLOGY LEVEL

3.3.2.4 General outcome

For all tested scenarios, we find that the ANSPs which control the biggest charging zones at the beginning of the simulation (i.e., the ANSPs with the highest market share in the first period) perform better in the long term, since they have more resources to invest at the beginning of the simulation, which results in faster technology adoption. On the contrary, the smallest ANSPs usually disappear between the second and the fifth auction as they are not competitive enough against the dominant ANSPs.

When there is a dominant ANSP controlling most of the market, thanks to its investment capacity and the economies of scale due to the possibility of reallocating ATCOs to different charging zones according to the labour requirements, both the total number of ATCOs and the average charge are lower than in the case where the market is controlled by more ANSPs. However, what seems a clear benefit in the short/medium-term, may lead to the emergence of an oligopoly in the long-term.

We find that:

- If the maximum market share is set to 30%, the competition between ANSPs increases as the total market is divided into a larger number of ANSPs. However, this could be too restrictive as the market share of France is already more than the 20% of the case study. Also, in the 30%-scenario, the ANSPs have less economic capacity to invest in the adoption of technology as in the other cases. Hence, we do not see lower charges as a consequence of more competition.
- When the maximum market share is set to 60%, the lowest charges are obtained, mainly due to economies of scale. However, two main ANSPs control more than the 90% of the market, which could lead to an oligopoly in the future.
- With a market share of 40% there is a significant level of competition (at least 4 ANSPs are competing in the analysed scenarios) and ANSPs have the economic capacity to invest on the adoption of technology.
- The auctioning order has an important effect on the tendering results, obtaining better bids for the countries that are first auctioned.

This suggests that the optimal performance of the tender is obtained with a maximum market share of 40% and auctioning the countries in a mixed order.

4 Provision of en-route air traffic services on a sector-less OD pair basis

4.1 Model description

4.1.1 Overall description

This model simulates a futuristic sector-less scenario in which ANSPs provide air navigation services to flights from origin to destination. As opposed to the mechanism described in section 3, where there was mainly competition for the market (with only limited competition in the market), in this institutional design there is full competition in the market.

In this model, ATCOs can work at any OD pair and ANSPs can provide air navigation services in all European regions. Hence, there is no preference to work on specific routes. The objective of the ANSPs is to maximise their profit.

Different options were considered to simulate this futuristic scenario, such as, for example, tendering the OD pairs to a group of ANSPs (competition for the market) which will, then, compete in the market of the specific OD or letting the airlines select an ANSP which will monitor their whole network. Finally, to explore this idea in a simple manner, we decided to simulate a market design similar to the electricity market, in which airlines submit their bids and ANSPs simultaneously submit their ask prices of controlled flight-kilometres to the Regulator, which chooses some price p that clears the market.

In this model, ANSPs have the incentive to invest in improving their efficiency and reduce their costs, otherwise their productivity relative to competitors will decrease and they may be out of the market.

4.1.2 Main assumptions and model restrictions

The following assumptions and restrictions have been considered:

- ATCOs may monitor any flight regardless the origin-destination it is flying.
- The complexity of monitoring every route is the same. The unit cost of monitoring a flight (€/km) is assumed to be homogeneous across all the OD pairs.
- The variation of costs due to charges is transferred completely from the airline to passengers, so airline demand varies according to the demand elasticity of passengers.
- ATCOs will have the same cost regardless of their nationality and will be employed by the same ANSP during all the simulation, unless they are dismissed. Since ATCOs may monitor flights regardless of their location, we have assumed that this would be the case in a sector-less scenario.

- When hiring new ATCOs, there is an initial extra cost due to training.
- When dismissing ATCOs, there is an extra cost due to dismissal costs.
- ATCOs have the same individual productivity regardless of their country, ANSP and experience. The difference of productivity between ANSPs is a parameter of each ANSP (technology level) and not an ATCO's parameter.
- If the financial capital of an ANSP is negative, it is not allowed to participate in a new auctioning process, since it is assumed that ANSP goes into bankruptcy.
- There are no new ANSPs entering the market. This is a limitation that could be eliminated in future versions of the model. In the scenarios presented in this study, this should not be particularly problematic, since ANSPs are not endowed with anticompetitive behaviours, and therefore they act as if they could be competing with newcomers.
- For the sake of simplicity, an average plane size, load factor and operational cost per kilometre are considered for all flights regardless of the origin-destination pair.

4.1.3 Model inputs

The following data are required as inputs to configure the model.

- Temporal horizon.
- Maximum market share [0-1].
- Time step duration.
- ANSPs' parameters (costs, number of ATCOs, productivity, growing parameter).
- Employment costs per ATCO-hour, dismissal cost, hiring cost and cost evolution.
- Demand forecast up to 2050. Different scenarios may be analysed (low, medium and high evolution scenario).

4.1.4 Geographical context

The geographical context provides the environment for the agents to operate in. The geographical context of this model is composed by a geographical charging zone in which the ANSPs may provide air traffic services.

4.1.5 Agents

The model includes the same three types of agents as in the previous model: ANSPs, Airlines, and the Regulator. Again, we first discuss the agents' characteristics and then the interaction rules.

4.1.5.1 Agents characteristics

4.1.5.1.1 Regulator

The role of the Regulator is to provide and store the public data created throughout the simulation (e.g., the charges of each period), announce the auction parameters (e.g., the maximum market share) and select the clearing price and capacity of the market in the auctioning process.

4.1.5.1.2 ANSPs

The ANSP agents are the main agents of the simulation. They make decisions to achieve their objectives according to their internal parameters, their competitors and the environment. They are modelled as profit-maximisers, but different objective functions could be implemented (see COMPAIR D4.1).

The parameters that define an ANSP are:

- Human resources (number of ATCOs).
- Financial capital: the capital available to the ANSPs to invest either in hiring ATCOs or improving their technology level, or to pay the cost of dismissing staff.
- Technology level. The higher the technology level, the more productive are the ANSPs.
- Investment percentage, which represents the percentage of the profit they will invest in each time step.
- Growth rate, which represents the maximum percentage with respect to its current size an ANSP can grow in a single time step.

4.1.5.1.3 Airlines

The airline agent is assumed to meet the total demand according to charges and the potential demand.

4.1.5.2 Agents' interaction rules

The sequence of agents' decisions and actions follows the scheme included in Figure 27.

The Regulator has the role of announcing the auction parameters, calculating the clearing price and allocating the demand to the winner ANSPs.

The ANSPs may submit several bids. Each bid is composed of two values: (i) number of flight-km; and (ii) the minimum unit-charge (€/km) the ANSP is willing to be paid for that quantity of flight-kilometres.

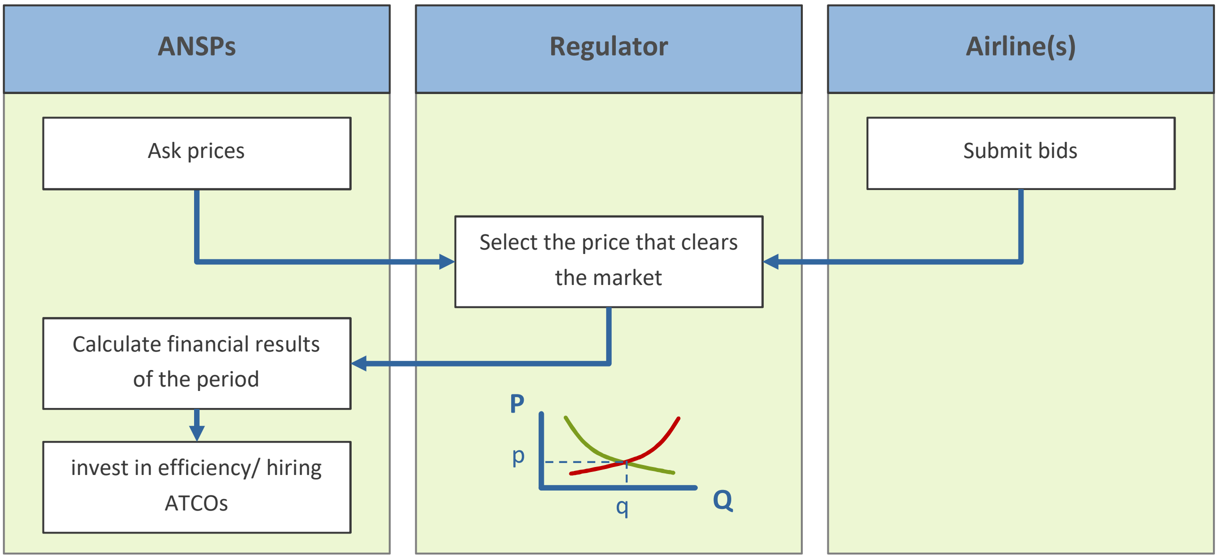


FIGURE 27 – SCHEME OF AGENTS' DECISIONS

I. ANSPs: Calculate ask prices

The ANSPs will submit two different bids.

The first bid corresponds to the maximum capacity they can afford with its current resources and the unit price that equalises the expected cost and the expected income.

$$Capacity_1(flightKm) = ATCOs_{current} \times working\_hours \times productivty \times flight\_speed \quad \text{EQ (22)}$$

$$productivity = \frac{flight\_hour}{atco\_hour} \quad \text{EQ (23)}$$

$$Cost_1 = StaffCost_1 \times IndirectCost + OtherCost \quad \text{EQ (24)}$$

$$Income_1 = Capacity_1 \times charge \quad \text{EQ (25)}$$

$$Charge_1 = \frac{Cost_1}{Capacity_1} \quad \text{EQ (26)}$$

The ANSPs will submit their true value since bidding the true value is a dominant strategy in this type of auction (uniform price), as in Vickrey auctions [22] . That is, the best choice of the bid is exactly the cost of the ANSP.

To explain this strategy, let's assume v_i is the bidder *i*'s true value for the good and b_i is the amount bid. Then the payoff of bidder *i* will be 0 if b_i is not the winning bid, otherwise the payoff will be equal to v_i - b_j, being b_j the market clearing price.

In this strategy behaviour, there are two cases to consider: $b_i > v_i$ and $b_i < v_i$. In both cases, the key point is that the value b_i only affects whether the bidder *i* wins or not the auction, but it does not affect how much *i* will get paid, which will be determined by the market clearing price.

1. $\boldsymbol{b_i < v_i}$. In this case, it only affects if bidder *i* would win with b_i but would lose with v_i. Then the highest other bid, b_k, must be between b_i and v_i, so bidder *i* would have a negative payoff ($b_k - v_i$).
2. $\boldsymbol{b_i > v_i}$. In this case, it only affects if bidder *i* would lose with b_i but would win with v_i. Then the highest other bid, b_k, must be between b_i and v_i, so bidder *i* would have non-profit, whereas he could have had a positive payoff ($b_k - v_i$) if bidding his own true value.

These arguments explain why truthful bidding is the optimal strategy regardless of what other ANSPs do. By bidding their true values, ANSPs ensure that the probability of winning the auction is higher than by bidding more than their true value and, if winning, they would get a positive payoff or, at least, they will not lose money (if bidding just the market clearing price).

Afterwards, ANSPs will submit a second bid with a different quantity and higher rate. Each ANSP will be modelled with a different "growth rate" parameter that represents how much they can increase their capacity in a single time step. In order to increase their capacity, ANSPs will have to hire new ATCOs. According to the growth rate parameter, the quantity of flight-km and the charge submitted in this second bid is calculated as:

$$Capacity_2 = \min\left[market_{share_{allowed}}, Capacity_1 \times (1 + growth)\right] - Capacity_1$$

$$Cost_2 = StaffCost_2 \times IC + OC + ATCOs_{hired} \times cost_{hiring}$$

$$Income_2 = (Capacity_2 + Capacity_1) \times charge$$

$$Charge_2 = \frac{Cost_2}{Capacity_2 + Capacity_1}$$

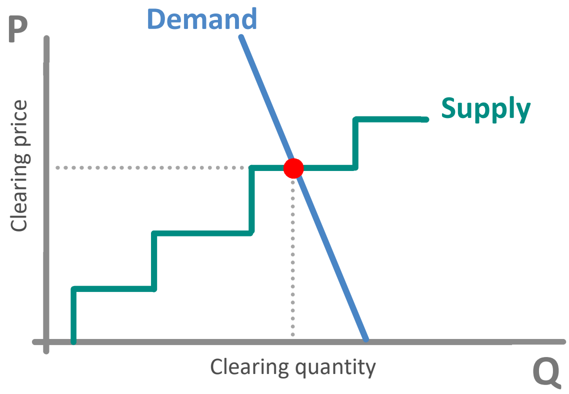
II. Airline: Estimate demand curve

In the model, it is considered that the variation in charges will be transferred completely to the passengers. It is assumed that the total cost of charges represents a 7% of the cost of the flight (Table 3) and the price elasticity for passengers is set to -0.6[1]. With these data, the passenger demand curve is estimated and the number of flights can be calculated accordingly.

III. Regulator: Select the market clearing price and quantity

The Regulator collects the bids from all ANSPs to construct the supply curve, receives the demand curve from the airlines and calculates the clearing price as the intersection of both curves.

The ANSPs which offer a price equal or lower to the clearing price will monitor as many kilometres as they proposed in the submitted bids and all of them will receive the same charge per flight-kilometre (equal to the clearing price).



IV. ANSPs: Calculate the financial results

In relation to the auctioning results, the ANSPs adjust their number of ATCOs and update their economic results to calculate the financial capital available to invest either in hiring ATCOs or improving their technology level. In this step, ATCOs may be hired or dismissed, which means an extra cost due to training/dismissal costs.

$$Cost_{staffadjustment} = ATCOs_{hired} \times Cost_{hiring} + ATCOs\_dismissed \times Cost_{dismissal}$$

$$Capital(t) = Capital(t-1) + Cost(t) - Income(t)$$

[1] Air Travel Demand. IATA economics briefing nº9 (2008)

V. ANSPs: Invest

The ANSPs will invest a percentage of their financial capital in order to improve their efficiency or increase their resources (number of ATCOs).

Depending on the results of the auctioning, different behaviours are modelled:

1. **The ANSP lost money in the last period**. In this case, since the ANSP is not efficient, it will invest all its capital in technology as the last option to be competitive with respect to its competitors.
2. **The ANSP did not lose money in the last period and its capacity is close to the maximum allowed market share**. These ANSPs will invest a percentage of its capital in improving their efficiency in order to reduce costs in future steps and to keep the market share.
3. **The ANSP did not lose money in the last period and its capacity is not close to the maximum allowed market share**. These ANSPs will invest a percentage of its capital in (i) improving their efficiency and (ii) hiring new ATCOs to increase rapidly its capacity.

4.1.6 Exogenous variables

The exogenous variables of the model include:

- Reference passenger demand: it defines a number of passengers at each simulation step and for each origin-destination pair if the charges are kept equal to current charges. Forecasted passenger demand is known by all the agents.
- ATM technology gains: it controls the efficiency gains that can be obtained by ANSPs by investing in new technologies.
- ATCOs’ cost: it defines the cost of a working hour of an ATCO.
- Fuel price.

4.2 Simulation scenarios

The proposed case of study simulates a hypothetical ATM market in which en-route air traffic services are provided on a sector-less OD pair.

4.2.1 General parameters

4.2.1.1 Geographic context

The network analysed, which includes the airspace of eleven countries of Western Europe, is presented in Figure 28.

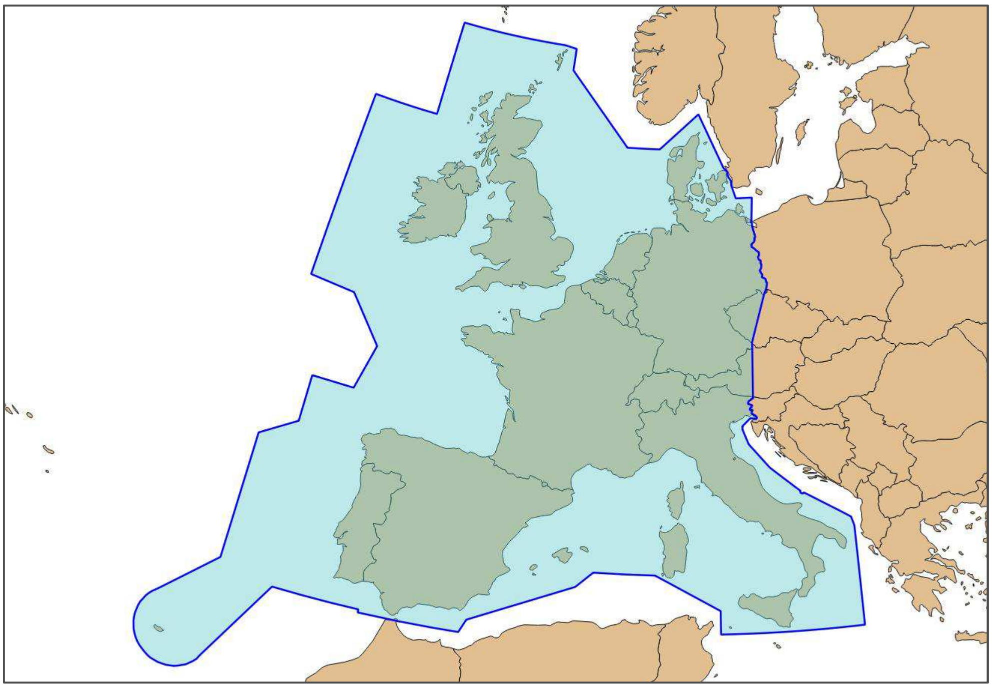


FIGURE 28 – AREAS ANALYSED IN THE CASE STUDIES

4.2.1.2 ANSP data

The ANSP data have been obtained from the ATM Cost-Effectiveness Benchmarking Report from 2014 [18].

The geographical context of the simulation includes the following ANSPs: Belgocontrol (Belgium), DFS (Germany), DSNA (France), ENAIRE (Spain), ENAV (Italy), IAA (Ireland), LVNL (Netherland), NATS (United Kingdom), NAV (Portugal), NAVIAIR (Denmark) and Skyguide (Switzerland), and MUAC (upper airspace in Belgium, Netherlands and Northwest Germany). The aggregate data of these ANSPs is shown in Table 9.

	Staff cost	Non-staff operating cost	Other cost
Total	2,821,756	632,988	898,603

TABLE 9 – ANSP DATA (FROM ACE REPORTS)

4.2.1.3 Temporal scope and time step

The temporal scope of the case studies is set to 2050, as in the previous model. To analyse in detail the evolution of the ANSPs, the time step is set to six months. Hence, every six months ANSPs are invited to participate in a new auctioning process.

4.2.1.4 Demand forecast

The demand forecast has been obtained from EUROCONTROL's report "Challenges of Growth 2013. Task 7" [19]. The data of the most likely scenario, the so-called "Regulated growth", which considers that the demand will grow 1.8% annually, have been employed in the following simulations.

4.2.2 Objectives of the simulation scenarios

The objective of the model is to analyse the outcome of different ANSPs' and auction's parameters such as the initial productivity and size of the ANSPs and the maximum market share. To this end we have modelled several scenarios by modifying these parameters.

4.2.2.1 ANSP parameters

ANSPs have different productivity and size when initialising the simulation. In this analysis, we will discuss the outcome of the ANSPs depending on their attributes.

4.2.2.2 Auction parameters

To analyse the outcome of different auction parameters, different scenarios are built by modifying the maximum allowed market share. The goal of establishing a maximum market share, calculated as the flight-km controlled by an ANSP divided by the total flight-km in the network, is to avoid the appearance of monopolistic or oligopolistic behaviours, as it ensures the existence of a minimum number of ANSPs.

We will analyse the outcome with three different values for the maximum market share: 30%, 40% and 60%, which will ensure the existence of at least 4, 3 and 2 ANSPs, respectively.

4.3 Analysis of results

4.3.1 ANSP parameters

We have run a simulation in which 10 ANSPs participate and the maximum allowed market share is set to 40%. All of them have a different number of ATCOs and different values of productivity which represents the flight-hours an ATCO can monitor in one hour.

DFS have assessed the feasibility of this sector-less ATM concept [21]. According to these results, the productivity of DFS in the simulation test was of 5.1 flight-hour per controller and an ATCO may be in charge of 6 aircraft. Since there is no much data about the productivity of ANSPs in a sector-less scenario, we have initialised the data of the ANSP with values in the range 3.0-3.9, higher than current productivity, and set the maximum productivity to 6.

The objective of the model is to analyse which ANSPs will dominate the market, if any, during the time frame of the simulation. The biggest ANSPs may have more economic power to invest in technology and become more efficient. On the other hand, the capital available for small ANSPs will be lower as their capacity to control flight-kilometres is reduced.

ANSP	ATCOs	Productivity (flight hour/ATCO hour)	Growth (percentage of growth every 6 months)
ANPS01	1100	3.0	5%
ANPS02	1050	3.1	5%
ANPS03	1000	3.2	5%
ANPS04	950	3.3	5%
ANPS05	900	3.4	5%
ANPS06	850	3.5	5%
ANPS07	800	3.6	5%
ANPS08	750	3.7	5%
ANPS09	700	3.8	5%
ANPS10	650	3.9	5%

TABLE 10 – ANSPS' PARAMETERS

According to the results obtained during the simulation, the ANSPs whose initial productivity is higher at the beginning of the simulation perform better. The market share of each ANSP during the simulation is depicted in Figure 29. It clearly shows that the most efficient ANSPs increase their market share progressively and the less efficient ones disappear from the market until a stable situation is reached by 2040.

Figure 30 represents the evolution of the productivity of ANSPs and indicates that the three dominant ANSPs achieve the maximum productivity. As ANSP07 is the less efficient ANSP at the end of the simulation, its bid is higher than their competitors, which means that its bid price is equal to the market clearing price. Hence, it does not obtain any profit to invest and upgrade its technology level.

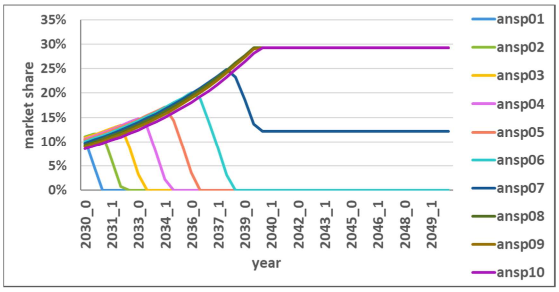


FIGURE 29 – ANSPS' MARKET SHARE

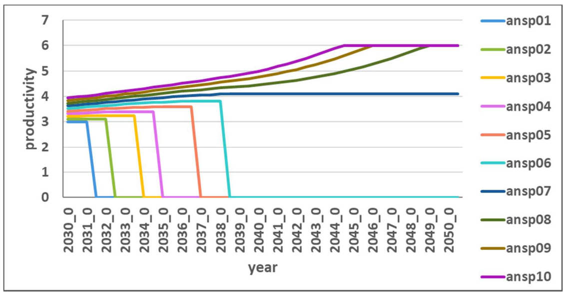


FIGURE 30 – ANSPS' PRODUCTIVTY

4.3.2 Auctioning parameters: market share

Three different values of the maximum market share have been analysed: 30%, 40% and 60%.

In the three simulations, the result obtained is that the market is consolidated into the minimum number of ANSPs possible (Figure 31). All ANSPs but one reach the maximum market share and a minor ANSP gets the remaining market share. It is also observed that the results in the 40% (60%) scenario seem to be the continuation of the 30% (40%) scenario if the market share were not limited to 30% (40%). This indicates that a maximum market share is needed in this type of simulation. Otherwise, an ANSP will control the whole market becoming a monopolistic ANSP.

It is also noticeable from Figure 32 that the dominant ANSPs achieve the maximum productivity within the time frame of the simulation.

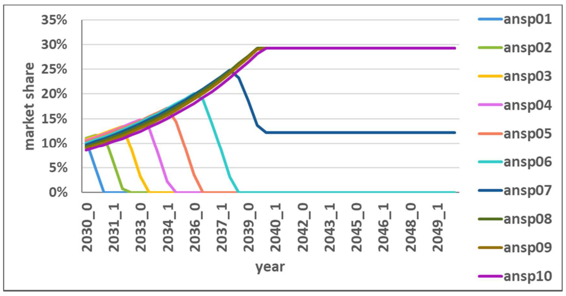


FIGURE 31.A 30%

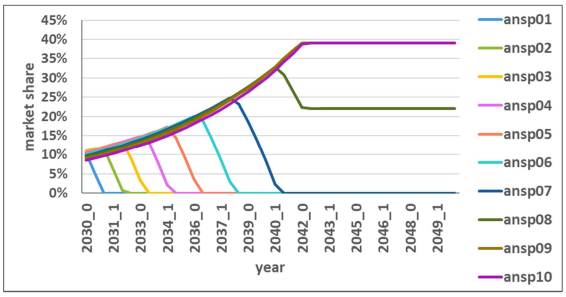


FIGURE 31.B 40%

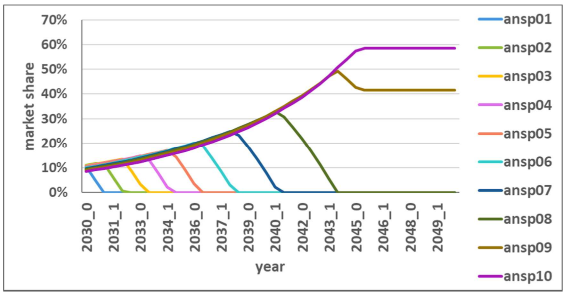


FIGURE 31.C 60%

FIGURE 31 – ANSPS' MARKET SHARE

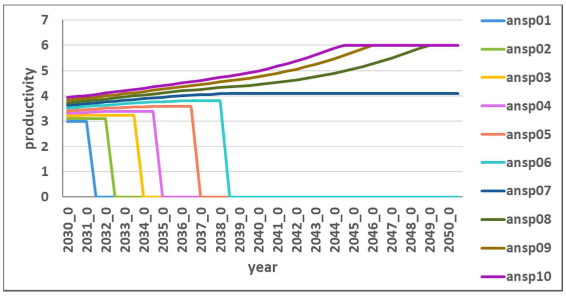


FIGURE 32.A 30%

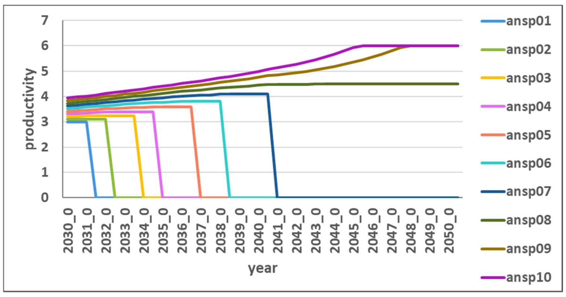


FIGURE 32.A 30%

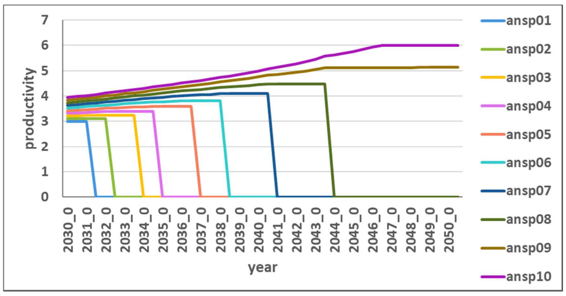


FIGURE 32.A 30%

FIGURE 32 – ANSPS' PRODUCTIVITY

The network charge of each period is illustrated in Figure 33. It can be noticed that, once the market remains stable, that is, the number of ATCOs in the market does not vary, the network charge remains constant. This is due to the fact that the least efficient ANSP set the market clearing price such that it does not get any profit to invest in upgrading its efficiency. Hence, this ANSP cannot offer lower bid charges in the following auctioning processes.

However, the maximum allowed market share does not have an influence on the total number of ATCOs (Figure 34) as the dominant ANSPs achieve the maximum productivity in the three scenarios.

Figure 33 – Network charge

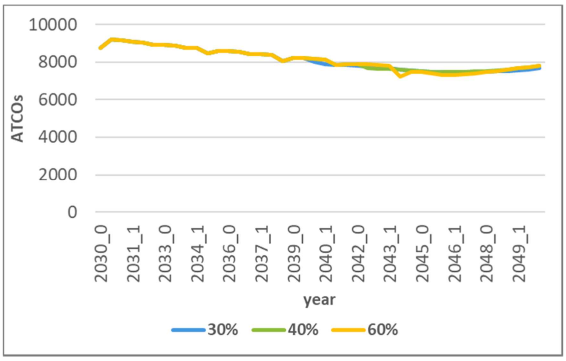


Figure 34 – Total number of ATCOs

5 Conclusions

In this document, we have presented two agent-based models designed to investigate the impact of two institutional designs: (i) the tendering of licenses to provide en-route air traffic services in specific geographical areas; and (ii) the provision of en-route air traffic services on a sector-less OD pair basis.

The first model evaluates the effect of auctioning parameters on the outcome of a hypothetical tendering of licenses to operate air traffic services within Europe. The model simulates the behaviour of a group of ANSPs which compete for the control of different charging zones to maximise their profit and airlines that aim to meet the demand minimising their cost. The ANSPs have been endowed with learning and adaptive behaviours aimed to calculate the bids according to their actual status and the previous bids of their competitors. The model has been applied to a simplified scenario which simulates the tendering of licenses in Western Europe at national level and illustrates the effect that (i) the frequency of auctions, (ii) the maximum market share and (iii) the order in which the charging zones are auctioned have in the network.

The model suggests that one of the main factors that drives the effectiveness of the ANSPs is the bidding strategy they follow. In the short and medium-term it seems that the Gates and the Fine bidding strategies perform better in terms of profit, despite having a lower market share Nevertheless, in the long-term, the Friedman strategy is demonstrated to be the dominant strategy. It also demonstrates that the ANSPs controlling the biggest countries when liberalising the market have an advantage due to their higher potential to invest in new technology.

With regard to the auction parameters, the scenarios evaluated proved that the main parameter which influences the outcome of the tendering both in the charges and the market share of the ANSPs is the maximum allowed market share. A high maximum market share favours the existence of big ANSPs which can benefit from economies of scale, but could lead to an oligopoly in the long-term. The order in which the countries are auctioned has a great impact on the local charges of each country, but its global network effect is not so important. Finally, the duration of licenses shows different outcomes but there is not a clear evidence to assert which one would lead to better results.

In future steps, the model could be enhanced with several extensions. Different investment strategies could be implemented so that the ANSPs select the amount to invest depending on their status and the environment conditions. More complex and realistic scenarios can be modelled by considering uncertainty in the environmental conditions (i.e., the demand and the fuel price). This will allow the study of the ANSPs adaptability to cope with changing and unexpected conditions with different degrees of volatility. Heterogeneous airline agents empowered with learning capabilities, so that they could improve the estimation of costs according to the passenger demand, could be introduced. This would allow us to investigate the impact of the cost of congestion and the daily distribution of flights. Moreover, behaviours other than profit maximisation in the ANSPs may be examined, such as anticompetitive practices. Also, more experiments could be conducted considering the whole Europe and the possibility of ties between ANSPs. Finally, it would be interesting to compare the outcome obtained with different type of auctions, in particular single-unit auctions (i.e., the present case) vs. combinatorial auctions in which all the areas are tendered at the same time and ANSPs bid for different combination of charging zones. This would allow us to investigate the trade-offs between the economies of scale offered by the combinatorial auction versus the presumably more effective learning process enabled by a sequence of single-unit auctions.

The second model presented in this document analyses a futuristic sector-less scenario in which ANSPs provide air navigation services to flights from origin to destination. To explore this idea in a simple manner, we have simulated a market design similar to the electricity market, in which airlines submit their bids and ANSPs simultaneously submit their ask prices of controlled flight-kilometres to the Regulator, which chooses some price p that clears the market. The model simulates a group of ANSPs competing in the market to maximise their profit and an Airline agent which responds to the charges of ANSPs. The model has been applied to a simplified scenario which reproduces the provision of en-route services in Western Europe and illustrates the effect that the ANSPs' parameters and the maximum allowed market share have on the outcome.

The model suggests that the most important parameter of ANSPs is their productivity, as the most productive ANSPs perform better during the simulation regardless of their size. This is due to their ability of bidding lower charges, which ensures them some profit in every time step. However, less efficient ANSPs cannot submit competitive bids and they end up being out of the market. Regarding the maximum market share allowed, the model shows that the market is always consolidated by the minimum number of ANSPs possible. Hence, a maximum market share is needed in this type of market to avoid a monopoly/oligopoly situation.

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Annex I. Tendering simulation scheme

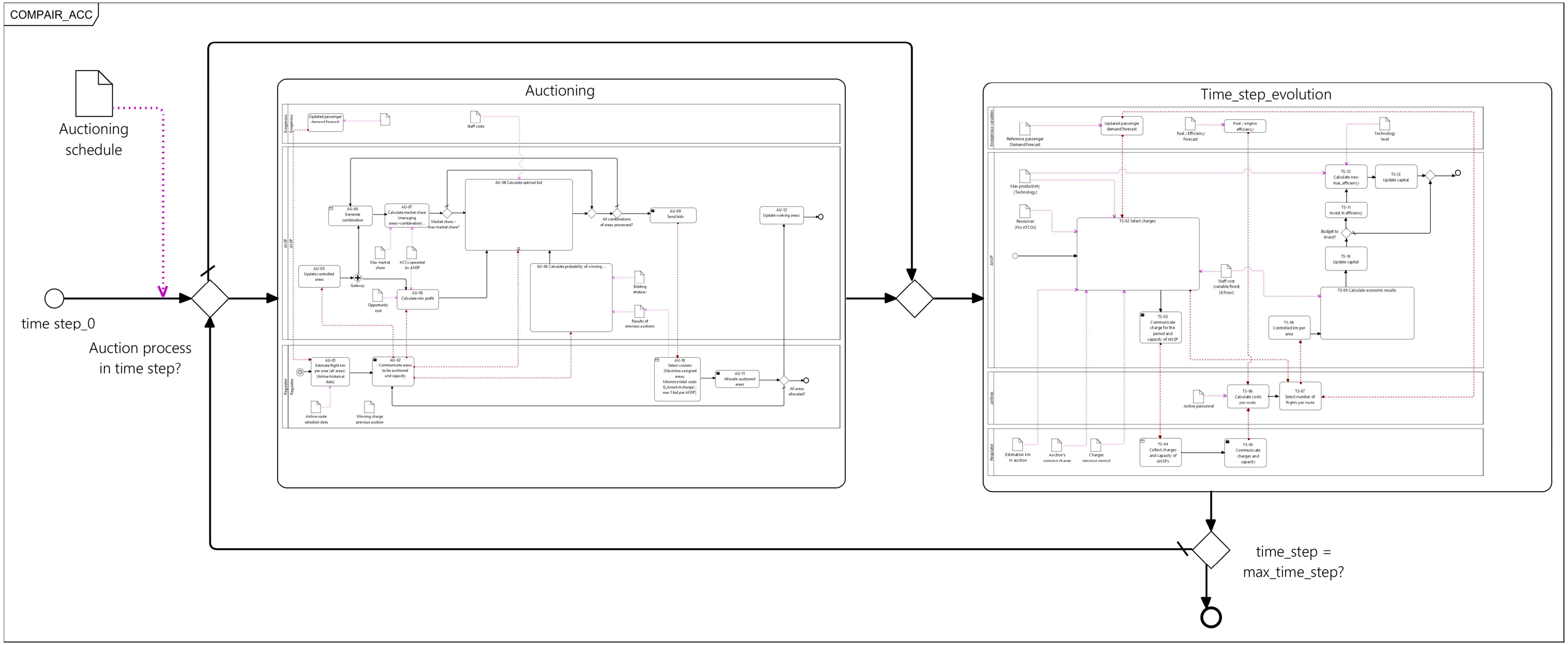

FIGURE 35 – TENDERING SIMULATION SCHEME

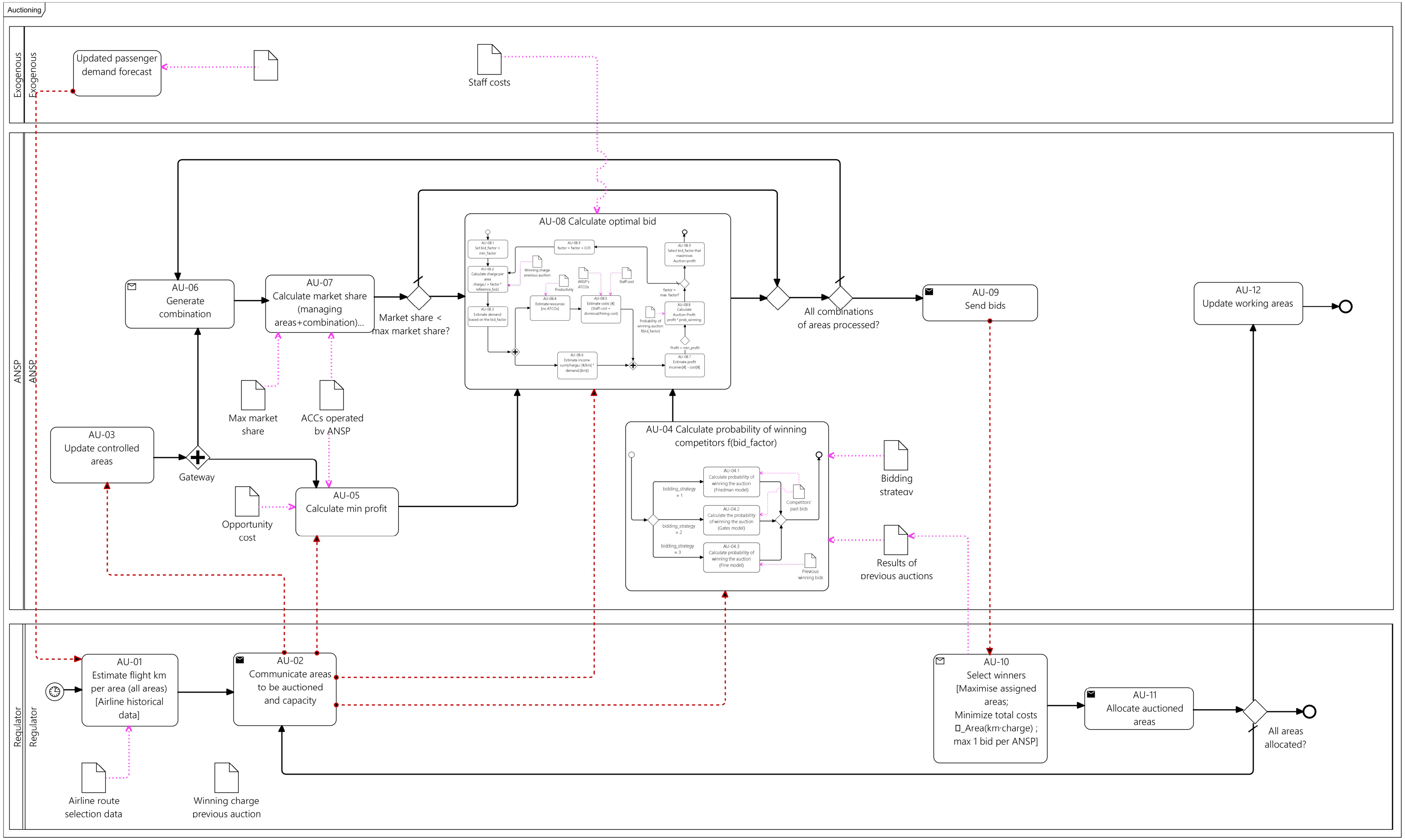

FIGURE 36 – AUCTIONING PROCESS SCHEME

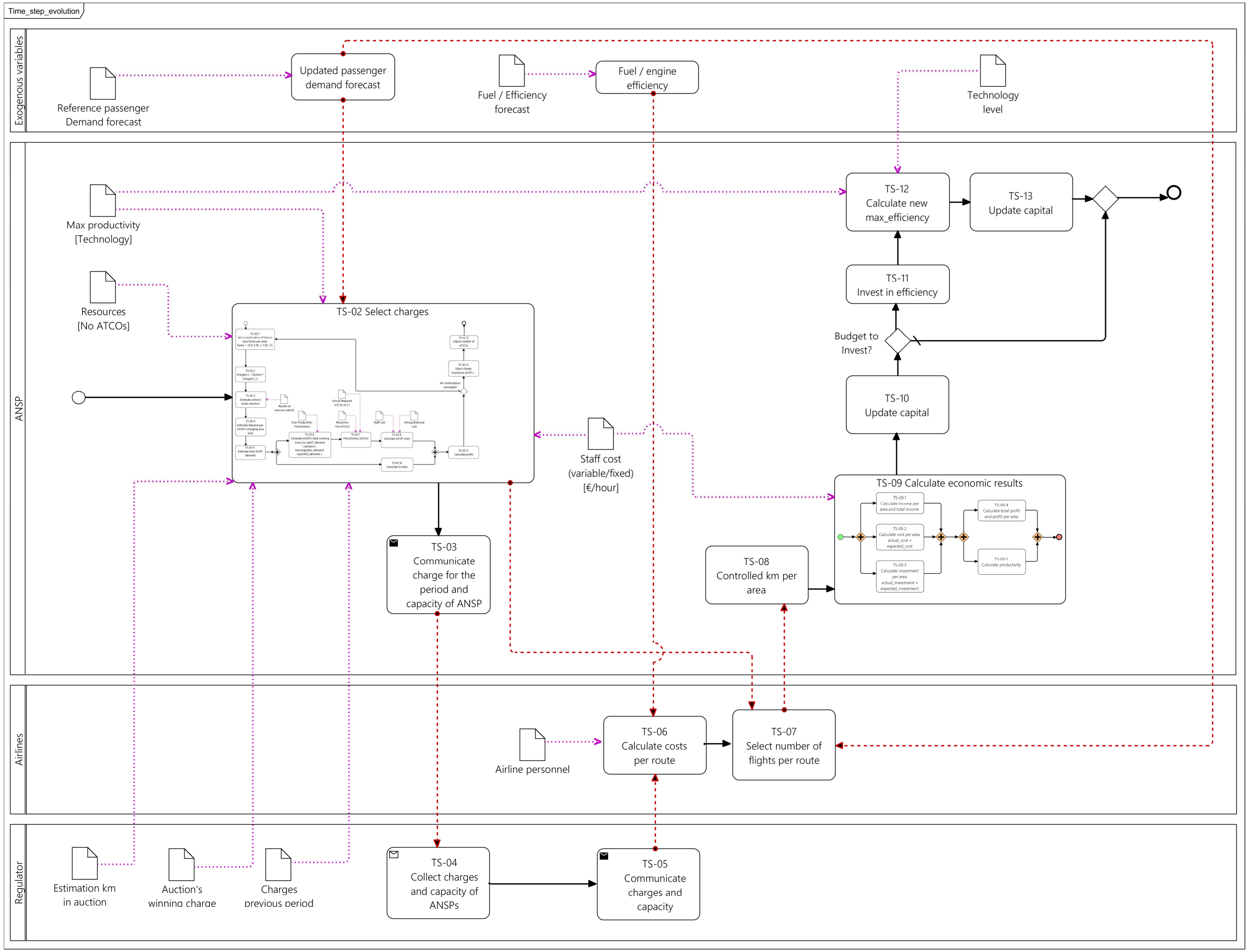

FIGURE 37 – EVOLUTION PROCESS SCHEME