Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo, and M. Loper, eds.

TECHNOLOGY ADOPTION IN AIR TRAFFIC MANAGEMENT: A COMBINATION OF AGENT-BASED MODELING WITH BEHAVIORAL ECONOMICS

Bill Roungas
Jayanth Raghothama

KTH Royal Institute of Technology
Hälsovägen 11c, Huddinge
Stockholm, 14157, SWEDEN

Miguel Baena
Oliva García-Cantú Ros
Rubén Alcolea
Ricardo Herranz

Nommon Solutions and Technologies
Plaza Carlos Trías Bertrán 4, 2ª planta
Madrid, 28020, SPAIN

ABSTRACT

The European Air Traffic Management (ATM) system is responsible for the safe and timely transportation of more than a billion passengers annually. It is a system that depends heavily on technology and is expected to stay on top of the technological advancements and be an early adopter of technologies. Nevertheless, technological change in ATM has historically developed at a slow pace. In this paper, an agent-based model (ABM) of the ATM technology deployment cycle is proposed. The proposed ABM is part of a larger project, which intends to recommend new policy measures for overcoming any barriers associated with technology adoption in ATM. It is a novel and one of the first approaches aiming at simulating the adoption of technology in ATM that combines the organizational point of view, i.e. stakeholders' level, the focus on policy testing and the inclusion of behavioral economics aspects.

1 INTRODUCTION

Air Traffic Management (ATM) is an umbrella term used in aviation for describing all systems that enable an aircraft to depart from an airport, transit the airspace and eventually land at the destination airport. Particularly in EU, ATM as a system was responsible for the safe and timely transportation of more than one billion passengers in 2019. Despite the major disruption due to COVID-19 crisis, this is a figure that is expected to grow and consequently the demands from ATM will also grow. It is therefore an area which despite depending heavily on technology, is still required and expected to stay on top of the technological advancements and be an early adopter of technologies.

Nevertheless, technological change in ATM has historically developed at a slow pace. The reasons are multiple: the very demanding safety requirements, the coordination effort required to harmonize standards around the world, the interdependencies between ground and airborne technologies, the monopolistic nature of air navigation service provision and the relatively small size of the global ATM market compared to other technology markets are among the factors that explain, at least in part, why ATM technological modernization has traditionally followed a slow, evolutionary path. In recent years, the need to accelerate ATM technological change has become more and more evident: growing traffic demand and new market entrants, such as commercial drone applications, are rapidly pushing the ATM system to its limits, calling for disruptive solutions that are able to boost the performance of ATM operations. Emerging technologies, especially digitization and automation, have the potential to facilitate this urgently needed technological upgrade. However, technology evolution is a necessary but not sufficient condition; innovation is a complex phenomenon, which depends not only on the development of new technologies, but also on the existence of regulation and institutions able to facilitate and foster the implementation of such technologies. In other

978-1-6654-3311-2/21/$31.00 ©2021 IEEE

words, decisions that affect ATM as a whole are not just influenced by the technical and economical factors, but also by political, legal and social aspects (Zeki 2020).

This paper proposes an agent-based model (ABM) of the ATM technology deployment cycle. As a modeling method, ABM offers several features that make it particularly interesting for the study of innovation processes, such as the possibility to model agents' heterogeneity, the explicit representation of the agents' interactions, the possibility to endow the agents with non-rational behaviors and behavioral biases (e.g., loss aversion), and the ability to model learning processes, evolutionary behavior and path dependence (Zhang and Vorobeychik 2019). The novelty of the paper stems from the fact that scarcely any references, and hence relevant work, were identified in the field of ABM in ATM technology diffusion. The organizational point of view, i.e. stakeholders' level, the focus on policy testing and the inclusion of behavioral economics aspects, separately do not represent a new contribution; it is the first time though that such comprehensive approach, combining all these three aspects, is applied to the study of technology adoption.

The ABM proposed is focused on reproducing the mechanisms that drive the adoption and implementation of new ATM technologies. The model specification is the subject of this paper. The model includes a representation of all stakeholders identified as relevant for technology adoption in ATM; a non-exhaustive list includes air navigation service providers (ANSPs), airports, airlines, the network manager, aircraft manufacturers and ATM technology providers, labor unions and policy makers. The model represents the long-term evolution of the system (e.g., up to 2050), paying special attention to the coupling between slow and fast dynamics (i.e., how the cumulative effect of the system performance on short timescales ends up triggering long-term decisions, such as the decision to invest in new technologies), building on and extending approaches such as the one proposed by Torres et al. (2017).

In Section 2, the state-of-the-art on the application of ABM to the study of technology adoption is illustrated. In Section 3, the ABM model is presented. Finally, in Section 4, final remarks are made.

2 BACKGROUND WORK

In this section, different aspects of ABM are explored. First, behavioral economics are analyzed particularly with how they can improve agents' behavioral rules. Then, several applications of ABM in various sectors and ATM are presented as a means to further demonstrate the applicability and advantages of ABM in similar problems as well as illustrate the lessons learned.

2.1 Behavioral Economics in ABM

ABM's primary difference from other modeling methods, for example system dynamics, is that the stakeholders of the system under study, i.e. the agents, are modeled individually and not as a group with similar characteristics. As a result, a whole new set of challenges arise, since modeling agents realistically would imply assigning agent's heterogeneous human-like behavior. This is where theories from behavioral economics become applicable. The specific theories that are modeled in the ABM proposed in this paper are *i*. bounded rationality, *ii*. nudge theory, *iii*. time dimension theories, like memory, and *iv*. social dimension theories, like herd behavior and fairness.

2.1.1 Bounded Rationality and Information Asymmetry

Bounded rationality was first introduced by Simon (1957), in which he posited that there are certain limits to humans' thinking capacity for a number of reasons, like limited information, cognitive capabilities of the human mind, and time restrictions. As with many systems, in ATM, some pieces of information are available to the public and accessible by all stakeholders, while other pieces are confidential and only accessible from certain agents. This information asymmetry has the potential to influence greatly the decision-making process and thus should be modeled in each agent.

In addition, decisions should be categorized with regards to the time needed to make them. Strategic decisions usually have a long-term impact and depend on multiple factors, thus require more time to make. On the other hand, operational/tactical decisions might share some common characteristics with strategic ones, like impact, yet due to their nature, they usually require quick decision-making processes. In ATM, the adoption of a certain technology could be considered a strategic decision, while an example of an operational decision is the commencement of a strike.

2.1.2 Nudge Theory

Nudge theory proposes the use of non-mandatory positive reinforcements as a way to positively influence behavior and ultimately a decision making process (Thaler and Sunstein 2008). This positive reinforcement has been found to increase the probability of a certain decision been made. In ATM, nudge could be used to favor certain decision by providing them as the default option. E.g., in an aircraft which has 3 different options for ATM equipment, the desired option could be the default one.

2.1.3 Time Dimension

There are several ways in which time influences behavior and decision making; some examples that are relevant to the proposed ABM are i. hyperbolic discounting (Frederick et al. 2002), based on which present events are weighted more heavily than future ones, and ii. memory (Kahneman 2000), based on which humans tend to overestimate the outcome of a future action and neglect the poor results of past activities. Hyperbolic discounting could be implemented as a modification of the observed benefit by the company depending on the timespan of the reward. Memory can be applied to the feedback loop of information on each time step.

2.1.4 Social Dimension

One of the basic assumptions of economic theory that behavioral economics disregards is that humans make decisions in isolation or to serve only their own interest. There are several reasons for abolishing this fundamental assumption of economics, with the most relevant for ABM in ATM being i. herd behavior or as is known in game theory "information cascade" and ii. fairness. Information cascade is described as the tendency to adopt the decisions of others, especially when there is information asymmetry (Goeree et al. 2007); in the current ABM could take the form of a fashion effect similar to the ones investigated by Hamilton (2009) in the energy supply industry. Fairness in behavioral economics has the same meaning as in all other aspects of life and people's responses to positive actions are often kinder than a self-interest model would predict (Fehr and Gächter 2000); in the current ABM, this shift in reactions can be applied to the relationship between organizations and labor unions.

2.2 Applications of ABM in different sectors

Traditional models of innovation diffusion, such as the one proposed by Bass (1969), represent aggregated trends rather than individual decisions. These models are helpful to understand innovation diffusion, but they are not designed to answer what-if type questions and do not explicitly consider the variety of agents and the complex dynamics of the social processes that shape technology adoption. In addition, aggregated models are usually criticized for a lack of explanatory power, as they are not behaviorally based. To overcome these limitations, in recent years ABM has been increasingly adopted for the modeling of technology adoption and diffusion processes in different sectors, helping understand aspects such as the role of network topologies, strong and weak ties, and network externalities (Kiesling, Günther, Stummer, and Wakolbinger 2012). ABM has been used, for example, to simulate the diffusion of agricultural innovations and water resource use in Chile and assess policy options in the context of the Mercosur agreement (Berger 2001; Berger et al. 2007). In the transport sector, Zhang et al. (2011) investigated the factors that can speed up the diffusion of hybrid and electric vehicles in the US, Zhang et al. (2015) estimated the potential impact of SAV systems on urban parking demand, Günther et al. (2014) simulated the diffusion of a second-generation biomass fuel in the Austrian market, and Dugundji and Gulyás (2008) studied the effects of households' heterogeneity and interactions in the adoption of various transport modes. Innovations in energy and water consumption have been also investigated using ABM: Schwarz and Ernst (2009) modeled different types of households to simulate the diffusion of water-saving innovations in Southern Germany, Faber, Valente, and Janssen (2010) studied the adoption of micro combined heat and power (micro-CHP) systems in the Netherlands, and Rai and Robinson (2015) developed a model to study the adoption of residential solar photovoltaic. In construction management, Nnaji et al. (2019) studied the complex phenomenon of forecasting the adoption of innovations at an organizational level and their potential impact on work operations; the model consisted of two well established and complementary socio-cognitive theoretical models: the Technology Acceptance Model and Theory of Planned Behavior. In industry 4.0, Prause and Günther (2019) proposed an ABM to analyze the impact of governmental intervention on the Industry 4.0 and particularly to test the sensitivity of Industry 4.0 innovation diffusion speed and degree due to interventions such as promotion, educational support, technology networks (hubs), technology standardization and financial aid. Lastly, Gotts et al. (2019) explored the advantages and disadvantages of the expressivity of ABM in their application in socio-ecological systems and particularly focused on the problems of model transparency and validity.

2.3 Applications of ABM in ATM

In the field of aviation, ABM has been used in a number of research projects to better capture the mechanisms underlying the relationships between different stakeholders. Torres et al. (2017) developed an agent-based model to analyze the introduction of competition in the ATM market through the tendering of licenses to operate en-route air navigation services, by explicitly modeling ANSPs' decisions to invest in new technologies, as part of their strategy to compete in a liberalized market. Liu and Madlener (2020) used ABM to assess the aircraft market diffusion. The authors rather than focusing only on the profit-maximizing behavior of airlines in their decisions to adopt a certain technology, they included additional aspects, like environmental and flexibility concerns, in order to reflect on the complexities that airline operations face today. The model shows good compliance with historical data, which could prove helpful in terms of knowing the market potential and diffusion patterns for companies planning production and deliveries of airplanes, for airlines planning their fleet maintenance strategy as well as for policy makers with interest in the aviation industry. However, this model presents several limitations such as the binary adoption decision (adopt vs reject) for one singular aircraft model series, whereas in some cases, airline companies are choosing between several similar competing models. This fact being of special relevance due to the duopoly formed by Boeing and Airbus in this field. The spatial factor, not considered here, is of relevance due to pilots' or maintenance technicians licenses, e.g. in Europe licenses for Airbus models are more common than for Boeing models, deriving in lower associated costs for flights that operate within this territory.

In conclusion, despite the lack of references in this topic, insights could be gained from applications in other sectors with similar characteristics. Some examples of such characteristics are the monopolistic behavior of ANSPs, the high degree of competitiveness in the airline framework, the strict and seamless security requirements, to name only but few.

3 THE ABM MODEL

In this section, the modeling methodology of the ABM as well as its specifications are defined. ATM is a complex system; the challenge therefore is to abstract it enough, rendering its complexity manageable, yet not too much as to invalidate the model's explanatory power. The methodology incorporates: *i*. the hypothesis and assumptions, *ii*. the exogenous variables, *iii*. the agents' definitions, *iv*. the decision making process, and *v*. the model's outputs and KPIs.

3.1 Hypothesis and assumptions

The first step towards specifying the ABM is formulating the assumptions that constitute the basis of the model. Assumptions are made for the model as a whole, the agents, the technology and the exogenous variables. With regards to the model as a whole, the focus of the study is on civil aviation, thus military aviation is not taken into account. Since military aviation usually ensures airspace security, this role is taken by each national government. Moreover, the adoption or rejection of a specific technology as a decision is made by the agents in each timeframe.

With regards to agents, the basic assumption is that they learn from previous experience as the simulation runs. Technology adoption by an agent can be partial; some examples to illustrate this concept are: i. an airline could adopt a certain technology only for certain routes, ii. an ANSP implements a technology only in a specific area control center etc. In addition, the economic and business aspects of technology providers is not considered in the model, except price definition. Finally, airlines city pairs are fixed, thus limiting the competition between them.

With regards to technology, the model focuses on deployment, hence disregarding the technical aspects of the previous phases, like research, development, certification and manufacturing. In other words, the technology is assumed to be developed and ready to be implemented. Yet, all these previous phases are considered in terms of time. For instance, a complex certification process will be emulated by providing a technology with a longer certification buffer time. Moreover, prices are set as constant a priori, but also enabling in the future to convert towards a dynamic pricing. In order to more realistically depict the influence of technology, certain technologies could have an impact on labor, like salary modification or even hiring or firing employees.

3.2 Exogenous variables

With regards to the exogenous variables, the basic assumption, which also derives from mathematics, is that none of these variables can be influenced or modified by the agents or their actions. Consequently, the GDP, population and fuel price forecasts cannot be modified by the evolution of the agents in the model. The labor unions and technology providers cannot lobby for their interests in the elaboration of the policy. It should be noted that traffic demand is not considered an exogenous variable and is influenced by the GDP, population changes and airlines prices. The identified exogenous variables are the following, i. policy measures and regulations to be tested by the model (e.g., flexible charging regulation, subsidies for ANSPs, etc.), ii. GDP growth (country level), iii. population growth (country level), iv. passenger demand, v. fuel price, vi. Engine efficiency, vii. unitary labor costs (per country, agent and position), viii, technology, ix. Black Swan events (e.g. coronavirus crisis).

3.3 Agents' Definitions

ATM is a complex system that involves multiple agents in different hierarchical layers. Moreover, agents can be categorized in different groups according to their objectives and the decision they have to take in the process of technology adoption. The agents identified in ATM are ANSPs (en-route and terminal), airports, airlines, network manager, technology providers, aircraft manufacturers, policy makers, safety agencies, funding agencies (CEF and national funding agencies) and labor unions. The different groups with their objectives and common decisions are summarized in Table 1. Aircraft manufacturers, safety agencies and any sort of national or European funding agencies are not modeled a priori, hence the tasks of the first are included in the technology provider agent, while the last two of those are grouped under the Regulators. Similarly, in this model, network managers act as a technology adopter ANSP and they possess a leader role, regarding technology adoption. Their monitoring and potential regulatory tasks are reflected in the policy maker agent. It should be finally noted that the primary objective of agents in the adopters group is whether or not they will adopt a specific technology. Below, the modeling methodology for each agent is described in more detail, while a graphical depiction of the model is shown in Figure 1.

Table 1: Groups of agents with their objectives and decisions.

Groups	Agents	Objectives	Decisions
Adopters	ANSPs, Airports, Airlines, Network Managers	Achieve an optimum result in their operational tasks while ensuring a minimum level as per industry standards (e.g., safety).	Technology adoption
Technology providers	Technology providers (ground/airborne, including aircraft manufacturers)	Provide a set of ATM technologies to the adopters	Set market prices
Regulators	Policy Makers, Safety Agencies, Funding Agencies	Monitor and execute the applicable policies in order to ensure the global welfare	Decisions derive from the policy in case and its compliance by the adopters
Labor unions	Labor unions	Lobby adopters in order to defend the labor conditions of their guild	Obstruct or support a deployment

3.3.1 Air Navigation Service Providers (ANSPs)

There are two type of ANSPs, en-route and terminal, differentiated by the flight phases they are in charge of. They share many common features but they also have some distinct differences. The role of the former (ANSP en-route) is to manage air traffic, by primarily providing ATM services to the airspace users (mainly airlines). The role of the latter (ANSP terminal) is to provide air navigation services (ANS) specifically related to approach ANS (ascending and descending) and aerodrome ANS (landing, take-off and taxi operations). This distinction is important since terminal ANS have been partially or fully privatized to other certified entities in many countries.

Other than these differences, the objectives, decisions and interactions between the two types of ANSPs are almost identical:

- Their objective is to balance KPAs regarding the safety, environment, airspace capacity (delay) and cost efficiency. Privately owned ANSPs have the additional objective of optimizing their profits while complying with minimum KPAs levels.
- The decision of adopting new ATM technologies, with better performances, will help them to comply with their goals. Other decisions are related to the capacity allocation, air traffic control charges and human resources aspects, like labor agreements and contracts.
- The interactions of ANSPs with the other agents in the model can be summarized as follows:
  - Airlines: ANSPs provide ATM services to airlines in exchange for navigation charges.
  - Technology providers: ANSPs acquire technology developed by technology providers.
  - Network Manager: ANSPs coordinate with the network manager regarding the technology acquisition.
  - Other ANSPs: ANSPs coordinate with other ANSPs regarding the technology acquisition.
  - Labor Unions: Human resources decisions related to the operations of ANSPs are influenced by labor unions.
  - Policy Makers & Regulators: Technology adoption, deployment times and the overall financial decisions are influenced by the decisions of policy makers and the requirements imposed by funding and safety agencies.

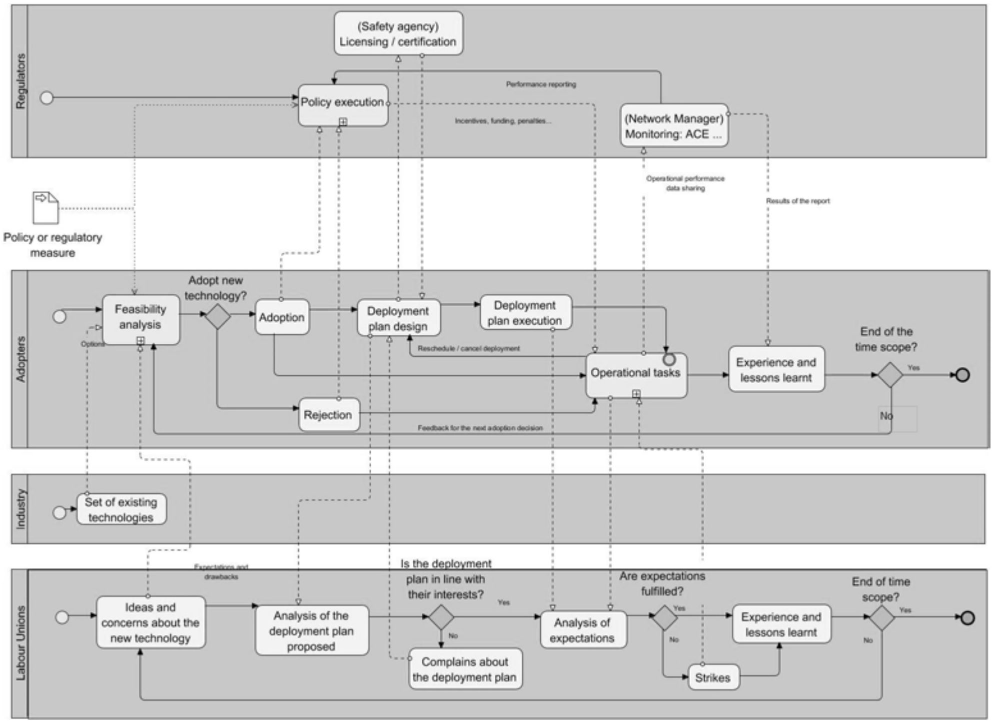

Figure 1: A graphical depiction of the ABM for technology adoption in ATM.

3.3.2 Airports

Airports are the interface between land and air traffic and the base for airlines. Airports offer several services (landing, aerodrome services, passenger services, parking, terminal use, etc.) the cost of which is included by airlines in the ticket price passengers pay for. Their objectives, decisions and interactions with other agents modeled in this study are:

- The objectives of an airport are to provide the best possible service and to maximize its profits, especially those managed by private companies.
- The main decisions, apart from decide on technology adoption are to define the charging fees for the services it provides, to decide on tendering the tower ATC and to plan for any capacity increase, like a new runway.
- The interactions of airports with the other agents in the model can be summarized as follows:
  - Airlines: airports are the interface between airlines and their passengers. Landing charges are established for the use of an airport.
  - Technology providers: airports acquire technology developed by technology providers.
  - Labor Unions: Human resources decisions related to the operations of ANSPs are influenced by labor unions.
  - Policy Makers & Regulators: Technology adoption, deployment times and the overall financial decisions are influenced by the decisions of policy makers and the requirements imposed by funding and safety agencies.

3.3.3 Airlines

Airlines are the most well-known actor of ATM in the public. Airlines transport passengers and freight with safety and in time from their origin to their destination. They are the main users of the airspace. Their objectives, decisions and interactions with other agents modeled in this study are:

- The main objective of an airline is to maximize profits.
- Airlines main decisions revolve around three areas. First is the network planning, where decisions like the frequency of flights, the destination airports and other strategic decisions take place. Second is the adoption of technology with regards to aircrafts, like the acquisition of a new plane or the renewal of equipment in existing planes. Third is the routing, where the routes that planes follow are determined based on different factors like the ANSP charges and efficiency (e.g., expected delay) and fuel costs.
- The interactions of airlines with the other agents in the model can be summarized as follows:
  - ANSPs: provision of ATM services and payment of navigational charges.
  - Airports: airports are the interface between airlines and their passengers. Landing charges are established for the use of an airport.
  - Technology providers: airlines acquire technology developed by technology providers.
  - Labor Unions: Human resources decisions related to the operations of airlines are influenced by labor unions.
  - Policy Makers & Regulators: Technology adoption, deployment times and the overall financial decisions are influenced by the decisions of policy makers and the requirements imposed by funding and safety agencies.

3.3.4 Technology Providers

Technology providers are in charge of developing and implementing new technologies. Their objectives, decisions and interactions with other agents modeled in this study are:

- Their primary goal is to maximize their profit and in order to accomplish that the technologies they bring forth should be in a large extent eventually adopted. It is therefore crucial for their success to efficiently evaluate the expected adoption of each technology.
- The main decision they are faced with making are price modulation and the pace of innovation of new technologies.
- Technology providers interact in the model with all the agents within the adopters' group, by providing them new solutions.

3.3.5 Policy Makers

The role of policy makers is to design and execute policies and subsequently monitor the compliance in these policies. In this model, the policy maker agent has a role similar to an "orchestrating agent". Policy regulations are treated as "initial conditions" in the simulation. Therefore, the policy maker's role is based on supervision, monitoring and execution of predefined rules given by the policy measure tested. Due to the scope of this model, agents are based only on European bodies, like EC and SESAR. Their objectives, decisions and interactions with other agents modeled in this study are:

- Their primary goal is to optimize the KPIs concerning distributional effects and aggregated global welfare.
- The decisions policy makers make are across all the domain of ATM and depend almost solely on the policy in case. Some examples of these decisions are forcing price-caps on ANSP charges, conducting a yardstick competition comparing the costs for setting the ANSPs' charges, defining the payment of Airspace users based on their performance, to name only but few.
- Policy makers interact will all the agents involved in the simulation.

Table 2: Decision making heterogeneity in the adopters' group.

Agent	Type	Features	Effect on decision-making process
Airline	Legacy	Aim of giving top quality services. Hub & spoke networks. Larger resources compared to LCC.	Keen on improving ATM services for giving top quality performance to the passengers.
	Low cost	Working with lower margins, thus more sensible than legacy carriers to delay indemnisations. Point to point networks.	Keen on improving ATM services to avoid indemnisations. The available resources to do so are limited.
Airports	Small size	Limited resources. Lack of expertise in developing technology. Strong dependence on airlines and regional government incentives to airlines (hidden subsidies).	Leads to outsourcing.
	Big size/ Hubs	Interested in R&D but not very active in the air-side innovation. Strong dependence on airlines.	Earlier incorporation of new technologies compared with small size airports.
ANSPs	Public	Unit rates regulation. Cost effectiveness driven performance. Subject to financial restrictions.	Performance improvement and regulations drives the decisions in first place.
	Private/ semi-public	Unit rates regulation. Profit maximization.	CBA and regulations drives decisions.

3.3.6 Labor Unions

Labor unions defend the interest of the groups of employees they represent (e.g., pilots, air traffic controllers, etc.). Their modus operandi is to put pressure on the decisions, with the aim of delaying the deployments, since in many cases new technologies equate with less need of certain personnel. Apart from putting pressure on the companies the employees they represent work, they also lobby with governments and policy makers as a means to put further pressure on the aforementioned companies. Their objectives, decisions and interactions with other agents modeled in this study are:

- The main objective of labor unions is to maintain and if possible improve the labor conditions.
- The decisions they usually make are either for the obstruction or support of the deployment of a new technology or whether the union and subsequently the employees it represents go for a strike.
- Labor unions interact with all the adopters in the simulation, influencing their operational tasks.

3.4 Decision Making Process

There is a clear distinction in decision making theory between individual and organizational decision making. While this study is concerned with organizational decision making, since every agent represents a company with specific objectives and agenda, several aspects of individual decision making are also considered. The reason is that decisions in an organizational level are made from people (managers, policy makers etc.) (Shapira 2002). This does not mean that the two areas of decision making are one and the same; it means

Table 3: Decision making heterogeneity in the adopters' group.

KPA	KPI
Safety	Effectiveness of safety management
	Application of RAT methodology
	Just Culture
Environment	Average horizontal en-route flight efficiency
Capacity	Average minutes of en-route ATFCM delay attributable to ANS
	Average minutes of arrival ATFCM delay attributable to terminal ANS
Cost-efficiency	Average union-wide Determined Unit Cost for en-route ANS
	Average union-wide Determined Unit Cost for terminal ANS
Technology adoption effectiveness	Time for adoption (global & country level per agent type)
	Market share of each technology (global & country level per agent type)
	Investment in technology adoption (global & country level per agent type)
Social welfare	Ticket price
	Number of strikes

that they are not two distinct and unrelated disciplines and that when contemplating organizational decision making, one cannot ignore aspects and insights from the individual decision making field.

Considering therefore the argument above, several factors that affect decision making should be considered. There is a wide range of such factors and some examples are *i*. the heterogeneity within each type of agent, *ii*. aspects from the field of behavioral economics, which is analyzed in more detail in Section 2.1, *iii*. situational factors unique to each case and scenario, *iv*. the characteristics of the technology developed, *v*. individual aspects, particularly those characterized as intrinsic, like leadership skill and innovativeness, and *vi*. exogenous variables, which are identified in Section 3.2.

The ABM proposed in this paper is particularly concerned with modeling the decision making process of adopters. In that regard, more details on how the different factors affect the decision making process of the three main adopters, with an emphasis on their heterogeneity, are shown in Table 2.

3.5 Model's Outputs and KPIs

The Single European Sky (SES) is a European Commission initiative that seeks to reform the European ATM system through a series of actions carried out in four different levels (institutional, operational, technological and control and supervision) aiming to satisfy the needs of the European airspace in terms of capacity, safety, efficiency and environmental impact. In turn, SES has defined several Key Performance Areas (KPA) and Key Performance Indicators (KPI), whose ultimate goal is to reflect the overall performance of the European ATM system (European Commission 2019). The outputs of the model are aligned with SES's KPA as well as with two additional KPA, technology adoption effectiveness and social welfare. These two KPA are captured through the outputs of the model attending both distributional and global effects. The qualitative insights that the model can provide are paramount for the objectives of this research. The goal is thus not to focus in the specific number of final adopters at the end of each simulation, but rather to obtain the effect of a given policy measure in both an aggregated/system and an individual/agent level. A summary of the different KPA and KPI are shown in Table 3.

4 FUTURE WORK & CONCLUSION

The work presented in this paper is just an intermediate step towards the final goal, i.e. the implementation of policies encouraging new technology adoption in air traffic management (ATM). The next step is the validation of the agent-based model (ABM) through behavioral experiments and participatory simulations (Roungas, Bekius, Meijer, and Verbraeck 2020). The participatory simulations will involve stakeholders from the European ATM industry, who have one-to-one correspondence with the main agents of the ABM. These stakeholders will interact with the ABM in two ways. The first way would be to assume the role of the agent that corresponds to their expertise, i.e. play in the model. The second way would be to tweak the parameters of the agent that corresponds to their expertise, i.e. play with the model. Both ways of interaction will be able to take place individually or in groups. “Individually” means that the stakeholder will be the only participant at this particular session and the remaining agents will be operated by the ABM itself. “In groups” means that more than one stakeholder will participate in a particular session assuming each the role of one agent, though it is not necessary that all agents in this case should be played by a human; the remaining agents will be played again by the ABM. This methodology enables the validation of the ABM both in an aggregated/system and in individual/agent level (Roungas, Meijer, and Verbraeck 2018a), allowing for insights in a micro and macro level that would otherwise not be possible.

In conclusion, in this paper, a novel ABM for technology adoption in ATM was proposed. The model combines aspects from behavioral economics, like bounded rationality and nudge theory, and a stakeholder analysis of ATM with the final aim of testing and eventually recommending policies that would encourage new technology adoption in ATM. The characterization of the work presented in this paper as novel is not done lightly. Firstly, research on technology adoption and diffusion in ATM using ABM is not just scarce but almost non-existent, with only Zeki (2020)’s work identified as both relevant and adequate. Moreover, similar research in other fields, like transportation, energy, industry 4.0 etc., in very few occasions incorporates all the aspects present in the ABM proposed in this paper. Finally, with regards to the future steps, the use of participatory simulations for ABM validation is yet another innovative aspect and admittedly one of the few methods that can capture the uncertainty derived from human behavior (Roungas, Meijer, and Verbraeck 2018b).

ACKNOWLEDGEMENTS

This project is funded by the SESAR Joint Undertaking (JU) under grant agreement No 893443, supported by the European Union’s Horizon 2020 research and innovation program and other SESAR JU members.

REFERENCES

Bass, F. M. 1969. “A new product growth for model consumer durables”. *Management Science* 15(5):215–227.

Berger, T. 2001. “Agent-based spatial models applied to agriculture: A simulation tool for technology diffusion, resource use changes and policy analysis”. *Agricultural Economics* 25(2-3):245–260.

Berger, T., R. Birner, N. Mccarthy, J. Díaz, and H. Wittmer. 2007. “Capturing the complexity of water uses and water users within a multi-agent framework”. *Water Resources Management* 21(1):129–148.

Dugundji, E. R., and L. Gulyás. 2008. “Sociodynamic discrete choice on networks in space: Impacts of agent heterogeneity on emergent outcomes”. *Environment and Planning B: Planning and Design* 35(6):1028–1054.

European Commission 2019. “Regulation 2019/317 - Performance and Charging Scheme in the SES”.

Faber, A., M. Valente, and P. Janssen. 2010. “Exploring domestic micro-cogeneration in the Netherlands: An agent-based demand model for technology diffusion”. *Energy Policy* 38(6):2763–2775.

Fehr, E., and S. Gächter. 2000. “Fairness and retaliation: The economics of reciprocity”. *Journal of Economic Perspectives* 14(3):159–181.

Frederick, S., G. Loewenstein, and T. O’Donoghue. 2002. “Time discounting and time preference: A critical review”. *Journal of economic literature* 40(2):351–401.

Goeree, J. K., T. R. Palfrey, B. W. Rogers, and R. D. Mckelvey. 2007. “Self-correcting Information Cascades 1”. *The Review of Economic Studies* 74(3):733–762.

Gotts, N. M., G. A. van Voorn, J. G. Polhill, E. de Jong, B. Edmonds, G. J. Hofstede, and R. Meyer. 2019. “Agent-based modelling of socio-ecological systems: Models, projects and ontologies”. *Ecological Complexity* 40(Part B):100728.

Günther, M., C. Stummer, L. M. Wakolbinger, and M. Wildpaner. 2014. “An agent-based simulation approach for the new product diffusion of a novel biomass fuel”. In *Agent-Based Modeling and Simulation*, 61–77. Palgrave Macmillan, London.

Hamilton, K. 2009. *Unlocking finance for clean energy: The need for ’Investment Grade’ policy*. London: Chatham House.

Kahneman, D. 2000. “Evaluation by moments: Past and future”. In *Choices, Values and Frames*, edited by D. Kahneman and A. Tversky, Chapter 38. Cambridge University Press.

Kiesling, E., M. Günther, C. Stummer, and L. M. Wakolbinger. 2012. "Agent-based simulation of innovation diffusion: A review Ant Colony Optimization-metaheuristic, method, and its application View project Multi-Objective Decision Support for Efficent Information Security Safeguard Selection (MOSES3) View project Elmar Kie". *Central European Journal of Operations Research* 20(2):183–230.

Liu, X., and R. Madlener. 2020. "The sky is the limit: Assessing aircraft market diffusion with agent-based modeling". *SSRN Electronic Journal*.

Nnaji, C., I. Okpala, and S. Kim. 2019. "A simulation framework for technology adoption decision making in construction management: A composite model". In *Computing in Civil Engineering 2019: Visualization, Information Modeling, and Simulation*, 499–506. Reston, VA: American Society of Civil Engineers (ASCE).

Prause, M., and C. Günther. 2019. "Technology diffusion of Industry 4.0: An agent-based approach". *International Journal of Computational Economics and Econometrics* 9(1-2):29–48.

Rai, V., and S. A. Robinson. 2015. "Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors". *Environmental Modelling & Software* 70:163–177.

Roungas, B., F. Bekius, S. Meijer, and A. Verbraeck. 2020. "Improving the decision-making qualities of gaming simulations". *Journal of Simulation*:1–14.

Roungas, B., S. A. Meijer, and A. Verbraeck. 2018a. "A framework for optimizing simulation model validation & verification". *International Journal on Advances in Systems and Measurements* 11(1 & 2).

Roungas, B., S. A. Meijer, and A. Verbraeck. 2018b. "The future of contextual knowledge in gaming simulations: A research agenda". In *Proceedings of the 2018 Winter Simulation Conference*, edited by M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, 2435–2446. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Schwarz, N., and A. Ernst. 2009. "Agent-based modeling of the diffusion of environmental innovations - An empirical approach". *Technological Forecasting and Social Change* 76(4):497–511.

Shapira, Z. 2002. *Organizational decision making*. Cambridge University Press.

Simon, H. A. 1957. *Models of man: Social and rational*. 1st ed. Wiley.

Thaler, R. H., and C. R. Sunstein. 2008. *Nudge: Improving decisions about health, wealth, and happiness*. Penguin Books.

Torres, J., D. Toribio, R. Marcos, O. G. Cantú Ros, and R. Herranz. 2017. "An agent-based auction model for the analysis of the introduction of competition in ATM". In *Proceedings of the 7th SESAR Innovation Days*, edited by D. Schaefer, 28–30. Belgrade, Serbia.

Zeki, E. 2020. *Assessing technology adoption in the European Air Traffic Management: The cases of virtual centre and flight-centric operations*. Phd, École Polytechnique Fédérale de Lausanne.

Zhang, H., and Y. Vorobeychik. 2019. "Empirically grounded agent-based models of innovation diffusion: A critical review". *Artificial Intelligence Review* 52(1):707–741.

Zhang, T., S. Gensler, and R. Garcia. 2011. "A study of the diffusion of alternative fuel vehicles: An agent-based modeling approach". *Journal of Product Innovation Management* 28(2):152–168.

Zhang, W., S. Guhathakurta, J. Fang, and G. Zhang. 2015. "Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach". *Sustainable Cities and Society* 19:34–45.

AUTHOR BIOGRAPHIES

BILL ROUNGAS is Postdoctoral Researcher at KTH Royal Institute of Technology, Sweden. His research interests focus on the modeling of interactive methods, like games, for the analysis of complex systems. His email address is vasroung@kth.se.

MIGUEL BAENA is an Aviation Consultant at Nommon. His email address is miguel.baena@nommon.es.

OLIVA GARCIA-CANTU ROS is the Chief Research & Development Officer of Nommon. Her email address is oliva.garcia-cantu@nommon.es.

RUBEN ALCOLEA is the Aviation Director of Nommon. His email address is ruben.alcolea@nommon.es.

RICARDO HERRANZ is the Chief Executive Officer of Nommon. His email address is ricardo.herranz@nommon.es.

JAYANTH RAGHOTHAMA is Assistant Professor of Healthcare Logistics at KTH Royal Institute of Technology, Sweden. His research interests focus on the intersection between simulation, gaming and design in complex systems. His email address is jayanthr@kth.se.