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Improvement of APOC Operations by using Simulation and Experimental Economics: Conceptual Approach

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Abstract

This work aims at developing an agent-based platform that allows to model and analyze decisions made by different stakeholders in an Airport Operations Centre. We will develop a methodology combining simulation, agent-based modelling and behavioral economics experiments for identifying the decisions and incentives behind decisions of the stakeholders in an Airport Operations Centre environment. Once, the causal decisions have been identified, these will be translated into an agent-based environment so, it will be possible to have a virtual environment for identifying which incentives are the best for aligning the objectives of the center, considering the diversity of objectives present in the system. The causal-relationships identified in the study will be validated with a human-in-the-loop environment already developed under the SESAR program. This study is an interdisciplinary one which integrates simulation, decision making and behavioral economics in the Airport Operations Center environment.

Keywords: ATM; airport; ABMS

1. Introduction

The world air traffic development rate for the following 20 years is forecasted as 4.4%, this gets out for additional limit in air terminals to suit future traffic (AIRBUS 2017). In order to use more efficiently the airport infrastructure, the following problems have been identified:

- Airport process are mostly independent from the network
- Operations are poorly predicted
- Due to the imbalance of traffic, restrictions are required
- Increasing block times
- Poor communication between stakeholders
- Decreasing efficiency of airport resources

To accommodate capacity and have a smooth operation it is necessary to change the management paradigm; for that reason, the Airport Operations Centre (APOC) has raised as an answer to the new necessities of coordination (EUROCONTROL 2018). A coordination arrangement at an airport, whereby operational stakeholders (actors) collaborate for the effective/efficient establishment and execution of an agreed operational plan, in a structured manner with agreed processes, either through physical or virtual interaction or a combination thereof. However, managing an airport involves using many resources and different actors participating altogether (airport operations, airlines, ANSPs) and they often operate in an environment where there is not a harmonized approach to collaborative airport planning. The APOC concept is a means by which the efficiency of overall airport operations may be addressed. However, as it has been already identified, collaboration is a must and it is required to make the concept work properly. The APOC has been implemented in different airports like Paris-Charles de Gaulle, London Heathrow and Amsterdam Schiphol.

The different roles of the APOC are divided into three sections (Fig. 1): Starting point Airside, Add-on L1 Landside and Add-on L2 Landside (EUROCONTROL 2018). The most important roles for the airport operations are the ones of the starting point airside that involves:

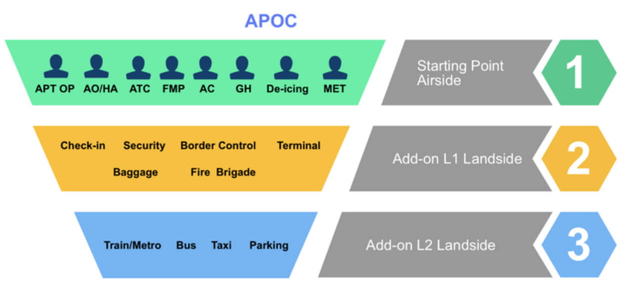

Figure 1. APOC Role

We will focus this study on the Starting Point Airside that involves the agents:

- APT OP: Airport Operator
- AO/HA: Aircraft Operator / Handling Agent
- ATC: Air Traffic Control Unit
- FMP: Flow Management Position
- AC: Airport Coordinator
- GH: Ground Handler
- De-icing
- MET: Meteorological Specialist

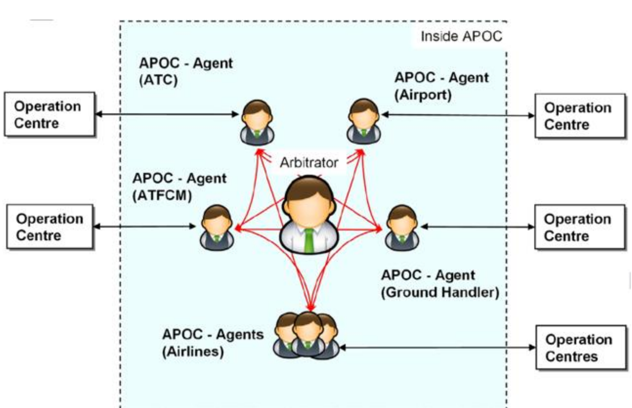

Figure 2. APOC Role representation

With this APOC system airport operation concepts, elements, procedures, and functions can be evaluated. For example:

- Airport Collaborative Decision Making (A-CDM)
- Route Planning Function (RPF)
- Variable Taxi Time Calculation (VTTC)
- Collaborative Pre-Departure Sequence Planning (CPDSP)
- Departure Management (DMAN)
- Demand and Capacity Balancing (DCB)
- Performance-Based Airport Management (PBAM)

Other areas in the scope of the APOC system are:

- Analysis of airport design, capacity, delay, performance, and quality-of-services
- Optimisation of aircraft pushback/pull/towing procedures
- Optimisation of operational processes and process flows
- Identification of operational bottlenecks

The APOC system currently comes with two major airport airside modules:

- Stand Management: the planning and control of the allocation of airport gates and buffer positions to aircraft. The APOC Stand Manager is based on the operational stand allocation rules and regulations of an airport (see figures above).
- Turnaround Management: the planning and control of the aircraft ground handling processes. The APOC Turnaround Manager is based on the operational ground handling procedures of an airport.

The APOC system is based on the A-CDM standards as described in the EuroCAE ED-141, ED-145, and ED-146 documents. The APOC system is fully based on freeware technologies like Java, Swing, and Eclipse and can run on any computer system. The APOC system has a Technology Readiness Level of about 4.

2. Agent-based Modelling and simulation

Agent-based Modelling and Simulation (ABMS) is a relatively novel approach to modelling systems comprised of autonomous, interacting agents (North et al. 2018). ABM promises to have far-reaching effects on the way that businesses use computers to support decision-making and researchers use electronic laboratories to support their research. Some have gone so far as to contend that ABMS "is a third way of doing science," in addition to traditional deductive and inductive reasoning (Macal et al. 2007). Computational advances have made possible a growing number of agent-based models across a variety of application domains.

An agent-based model has different autonomous agents that act on their own without external direction in response to situations the agent encounters during the simulation. Modelling a population of autonomous agents, each with its own characteristics and behaviors, that extensively interact is a defining feature of an Agent-Based Simulation (ABS). Agent-based simulation is most commonly used to model individual decision-making and social and organizational behavior (Banks et al. 2010). These notions of behavior, decision-making, and interaction apply to modelling many kinds of systems. Agents often represent people, or groups of people.

Regarding the attributes that can be present in agents, there are many kinds of agent attributes. Some common attributes used to represent people include age, income, sex, history, preferences and other characteristics related to the interest of the field of study. However, many agent attributes, such as preferences, are multifactorial and thus are defined at multiple, nested levels. In an agent-based simulation, these attributes are carried by each agent and can often evolve or change over time as a function of each agent's experiences.

Characteristics that have come to be associated with agents are:

- adaptive;
- have the capability to learn and modify their behaviors;
- autonomous;
- heterogeneous, resulting in a population of agents having diverse characteristics.

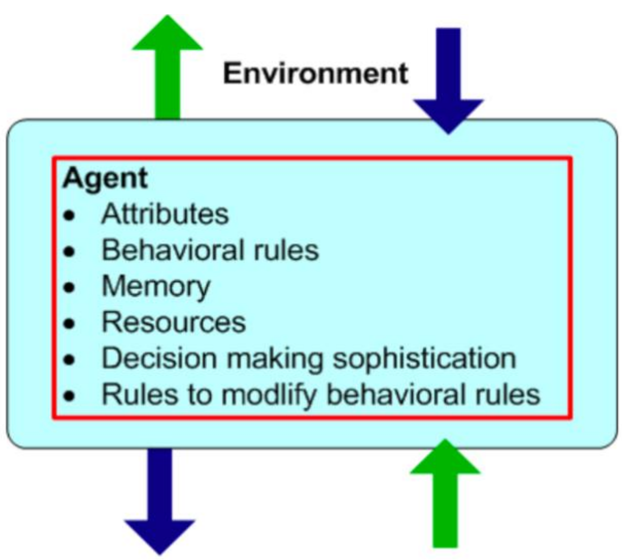

Figure 3. The architecture of an agent

The fundamental feature of an agent is the capability to make independent decisions. This requires agents to be active responders and planners rather than purely passive components (Macal et al. 2008).

- An agent is an identifiable, discrete, or modular, individual with a set of characteristics and rules governing its behaviours and decision-making capability. Agents are self-contained. The discreteness requirement implies that an agent has a boundary and one can easily determine whether something is part of an agent, is not part of an agent, or is a shared characteristic.
- An agent is autonomous and self-directed. An agent can function independently in its environment and in its interactions with other agents for the limited range of situations that are of interest.
- An agent is social, interacting with other agents. Agents have protocols for interaction with other agents, such as for communication. Agents have the ability to recognize and distinguish the traits of other agents.
- An agent is situated, living in an external environment with which the agent interacts in addition to other agents.
- An agent may be goal-directed, having goals to achieve (not necessarily objectives to maximize) with respect to its behaviours. This allows an agent to compare the outcome of its behaviour to the goals it is trying to achieve.
- An agent is flexible, having the ability to learn and adapt its behaviours based on experience. This requires some form of memory. An agent may have rules that modify its rules of behaviour.

Regarding the behaviors of agents, they have several behavioral features. These features include:

- Decision rules to select actions,
- Adaptation capabilities to learn from experiences,
- Perceptual capabilities to sense its surroundings,
- Optional internal models to project the possible consequences of decisions.

These behavioral features often vary from agent to agent to reflect the diversity commonly found in real situations. There are essentially two levels of agent rules. The first are base-level rules. These rules specify how the agent responds to routine events. The second level contains "rules to change the [base-level] rules" (Casti 1998).

These second-level rules provide adaptation by allowing the routine responses to change over time. Thus, according to Casti (1998), agents have "rules and rules to change the rules". Of course, this simple hierarchy can be greatly elaborated depending on the application.

Agents have sets of decision rules that govern their behaviors. These rules allow agents to interact with and communicate with other agents as well as to respond to their environments. These rules can provide agents with responsive capabilities on a variety of levels from simple reactions to complex decision-making.

Agent behaviors follow three overall steps:

- First, agents evaluate their current state and then determine what they need to do at the current moment.
- Second, agents execute the actions that they have chosen.
- Third, agents evaluate the results of their actions and adjust their rules based on the results.

These steps can be performed in many ways, including the use of simple rules, complex rules, advanced techniques, external programs, or even nested subagents.

3. Behavioral Economics

On the other hand, behavioral economics studies the effects of psychological, cognitive, emotional, cultural and social factors on the economic decisions of individuals and institutions and how those decisions vary from those implied by classical theory. Behavioral economics is primarily concerned with the bounds of rationality of economic agents (Kagel et al. 2016). Behavioral models typically integrate insights from psychology, neuroscience and microeconomic theory. The study of behavioral economics includes how market decisions are made and the mechanisms that drive public choice (Friedman et al. 1994). The three prevalent themes in behavioral economics are:

- Heuristics: Humans make 95% of their decisions using mental shortcuts or rules of thumb.
- Framing: The collection of anecdotes and stereotypes that make up the mental filters' individuals rely on to understand and respond to events.
- Market inefficiencies: These include mis-pricing and non-rational decision making.

Regarding behavioral economics there are important studies about coordination and public goods (Bouarfa et al. 2012). So, this motivate use of agent-based simulation models to analyze and forecast behavior of actors in the air transport system.

4. Methodology

We will use a methodological approach that combines simulation, agent-based modelling and behavioral economics for developing what we called 2nd generation simulation agents that are not only able to sense, think and act accordingly to their environment and externalities, but also apply decision-making internal models that are validated by field or laboratory experiments.

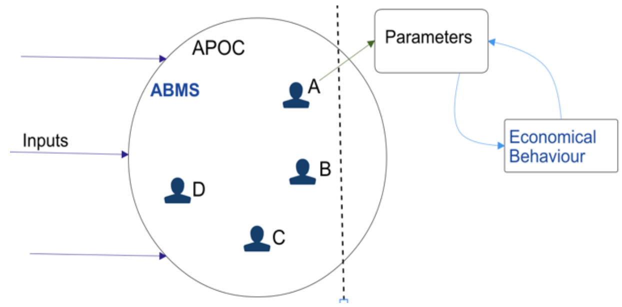

Figure 4. Interaction concept of agents in the APOC environment

Fig. 4 illustrates how the different agents will interact within the environment. First, we have the inputs that the APOC receives it could information about daily operations. All the different roles from the APOC receive this information so they have to make decisions for the operation, but these decisions would be analyzing the different parameters that affect the decisions but using economical behavior approach.

To exemplify what an agent is, we will describe one agent, the ground handler (TAMS Partners 2012). The main activities that the ground handler carry out are:

- Turnaround and departure punctuality
- Check-in processing and queue times
- First and last bag delivery
- Baggage delivery to aircraft
- Availability and duration of bussing
- Boarding and de-boarding times
- Obligation to comply with local Airport Rules and Regulations
- Insurance requirements sufficient to cover any losses to aircraft or infrastructure, determined on consultation with airport insurance broker
- Indemnities for any loss or damage
- Obligation to have a legal agreement in place with every aircraft operator prior to services being rendered, with such agreement at a minimum addressing issues of liability between the parties
- Obligation to ensure indemnity against industrial action
- Duty to report accidents and incidents, as part of the SMS (Safety Management System)
- Obligation not to withhold services
- Obligation to participate in relevant local safety, performance and quality committees or processes
- Emergency response participation
- Valid permitting or authorisation from airport operator
- Environmental requirements, i.e. emissions, fuel types
- Quantity to meet operational demands
- Age of equipment
- Servicing intervals
- Compliance with IATA recommendations, AHM 900
- Checks of safety critical vehicle components

Inside the APOC the inputs, tasks and outputs of the ground handler are represented with the Fig. 5.

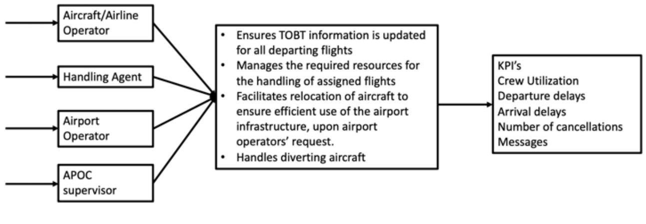

Figure 5. Ground handler tasks

The figures 6 and 7 represents the APOC interface that the ground handlers operate (Kjenstad 2019).

Figure 6. APOC Stakeholder GH

Figure 7. APOC Stakeholder GH 2

The motivation for studying these issues comes from the analysis of organizations made in behavioral economics and the need to find ways to combat organizational decadence and in particular in the APOC environment which is considered a crucial organizational change for improving efficiency in ATM.

The main hypothesis is that with the combination of these techniques, it will be possible to better align or find a balance amongst the different objectives present in the APOC like punctuality indicators, passenger service, turnaround times, throughput among others; with the final objective of improving the coordination and efficiency of the operation of an airport.

As an overview we will follow the next methodology.

Figure 8. Methodology phases

The methodology follows different phases (Fig. 8) in a horizon of three years. The structural approach will enable us to construct progressively the different elements and functionalities required for modelling the APOC on the one hand, and for parameterizing the agents on the other. The different steps to follow are:

1. Functional Specification of Actors: In this state, we will make a parameterization of the different actors that participate in the APOC, what is required to specify are the inputs, decision, functions and bargaining power for making the final decision for a specific situation. This phase consists of the conceptual definition of the different actors and how they will interact with each other and their environment. This phase depends on the conceptual definition of an APOC in reality.
2. Codification of Virtual environment: An environment will be codified where the actors can get external input and stimulus (disruptions) and based on their own objectives will try to make the best decision; during the decision process they will need to negotiate with the other actors to get to a final decision.
3. Verification of Agents: Once developed and codified, the initial logic will be verified by making different controlled experiments for the individual agents. This will allow to identify if the logic they follow is in accordance with reality
4. Validation: For this task, it will be necessary to perform a cross validation where some results from lab/field experiments are used for comparison of the results of the virtual environment.
5. Experimental design (policy making): This phase will consider the different architecture of experiments to be performed with the developed agents to identify potential collaborative policies and then later they will be performed in the human-in-the-loop environment.

5. Challenges and limitations

Literature review explains difficulties for the implementation of an APOC. First, the success of an operations center for the airport is determined by the collective willingness of airport actors to strive for a common goal (or goals). A high uniformity is desired in the approach of different airport scenarios. This uniformity can be reached through prescribed strategies, guidelines, and a clear role distinction.

For example, a common goal like striving for an optimum usage of runway capacity during peak hours is conceivable for all stakeholders. The implications of such a goal and its related constrains to all stakeholders should be understood and agreed on. Only then, collaboration has the chance to succeed.

The decision-making process in the APOC should be autonomous. Decisions must overrule control centers of individual stakeholders, in order to manage capacity orderly. By using planning and simulation tools, the APOC can provide an orderly and constant flow of trac. This lowers workload for operators and secures the stability of the airport system.

Also, the programming and the implementation is a challenge due to the complexity of the problems and the human behavior during the negotiations, the multiple goals, disruption and working with stress.

6. Conclusion

We have introduced the initial concept of the use of ABM with Behavioral Economics for developing a methodology that enable us the design of policies and the identification of incentives for increasing collaboration in the APOC environment. The methodology presented is a combination of techniques that have been proved to be efficient in their own knowledge areas; i.e. ABM for simulating individual agents and behavior of independent people/actors, behavioral and experimental economics for identifying how people make decisions in an economic environment and simulation itself as the overarching technique that enable putting together all the knowledge in a virtual environment.

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