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Capstone Final Project

[193022] Airline Workforce Scheduling based on Multi-agent Systems

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Abstract

This study addresses employee's scheduling problems of an airline company who are assigned to customer service at the airport. The problem can be defined as a dynamic scheduling problem that includes uncertainties and unexpected environmental changes. Therefore, this project proposes an agent-based simulation model that implements the workforce-scheduling problem including features such as skills, preferences, and restrictions that the airline could have. Besides to the workforce-scheduling problem, this research project also integrates the personnel transportation problem, which considers the personnel's route assignment from their household to the airport and back, concerning the welfare of the employees, upon certain shift conditions defined by the company. The integration and simulation of both problems seek to analyze and bring forward a solution that considers the relationship between both problems. Finally, using an agent-based model for the integration allows us to face a more complex problem and simulate it in a non-deterministic environment while consuming fewer resources than traditional optimization methods. The proposed model achieves to improve indicators at the Schedule and transport programming level. The model focused on generate schedules associated with routes efficiently, generating better decision-making, such as: minimizing variability values, missing of starting of shifts, unattended demand, total kilometers traveled by agents and the number of routes to use. It was evidenced that the scheduling of transport agents and scheduling associated with the better management of the indicators generated a better distribution of activities and therefore better satisfaction values.

Key words: Workforce Scheduling, Personnel transportation, Multi-Agent Systems, Agent-based scheduling, Optimization

1. Problem statement and Justification

1.1. Problem statement

A major area in the development of a country is a robust airport connection system because it influences the political, socio-economic, and technological aspects. Warren (2007), using data from 98 U.S. metropolitan areas, found that countries that have an airport with commercial air service tend to have a higher income, employment, population, dividends, interest, and rent. In effect, the airport system plays a vital role in responding to the passenger's demands of different operations, faced by the response plans of the airlines, which include the preparation of flights, attendance, and boarding of passengers, or control of departing and arriving flights, among other operations. Those operations include international, domestic, and various flights. International flights have an origin or destination in another country. Instead, domestic flights have an origin or destination inside the country, and both types of flights require different personnel assignments (i.e., language skills, knowledge of immigration policies, among others). Finally, several flights include operations that are not directly related to passenger transportation.

Additionally, in the second trimester of 2019 at El Dorado airport, 1'477.325 passengers flew internationally, 2'819.684 passengers flew domestically, and there were 75.056 various flights (El Dorado, 2019). Over the years, there have been issues concerning the provision of airline services in airports resulting in passenger dissatisfaction due to long waiting times, and, on the airline personnel side, work overload, lack of control over operations, and poor management of workforce scheduling. Also, there has been a lack of prevention of events, considering the highly dynamic behavior of flights and other airport operations.

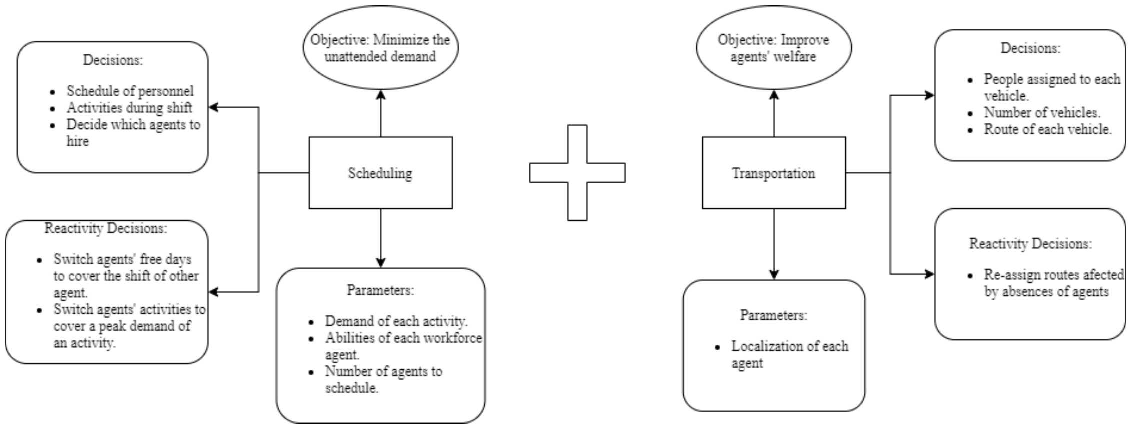
This research is aimed at developing an efficient and flexible workforce-scheduling model for an airline company. According to Hur et al. (2019), "*The vast increase in data over the last couple of years has shown that demand has volatile characteristics. In the airport environment, employee shifts are designed to cover the demand associated with flight schedules*." The main issue with these volatile demands is that it leads to a mismatch between the original workforce schedule and the demands being covered in the different airport operations. Additionally, a bad workforce-scheduling, on the side of the airport personnel, would produce an increase in job dissatisfaction, work overload, schedule variability, high personnel rotation, among others.

The critical problem in this company is the manual planning of employees to attend different customer service activities that need to be fulfilled, and this leads to an insufficient number of workers to take care of time-critical activities, such as, check-in, boarding, help desks, etc.

The problem is mainly composed of the following factors: the strategic problem of determining the optimal schedule for the workforce, the operational problem of weekly rostering, task assignment problem for the assigned workforce, and the assignation of transport vehicles. Also, to attend these problems efficiently, airlines must define starting hours, and which activities each employee must perform during the planning horizon. It is worth noting that the company has a considerable number of employees that are involved in the airport service and each of them has different abilities, preferences, and restrictions that the airline has to take into account during the decision-making.

As mentioned earlier, one of the main factors for decision making is the assignation of transportation for airline employees during specific timeslots established by the airline. Nowadays, moving from home to work or from work to home can be considered a problem when it comes to generating the workforce-scheduling because of all the unexpected events that can occur during the journeys. On the one hand, the decision making and uncertain events on scheduling directly affect the transport; for example, an activity could unexpectedly end late, so the transportation of the employee will be affected. On the other hand, transportation decisions and uncertain events could also affect the scheduling, for example, an employee could arrive late because the transport suffered an issue, in consequence, the planning of the day will be affected. In conclusion, the proposed model seeks to solve the workforce-scheduling of the airline while taking into account both problems to minimize the unattended demand of passengers and maximize the welfare of the employees by providing transportation in those timeslots that apply. The aforementioned can be summarized in *Figure 1*, which shows the objectives, parameters, and decisions for each problem.

Figure 1. Problem Description.



1.2. Justification

The coordination and management of workforce and human resources have always encountered issues. Nowadays, organizations seek to reduce adverse outcomes by implementing techniques that can help with those issues. Thus, the usage of a specific technique requires an assessment of the context, the quality of the solution, the time and effort for the decision making, and the level of automation desired. According to Maenhout (2010), "*efficient crew employment can drastically reduce operational costs of airline companies*" and highlights that developing an efficient workforce schedule is an essential factor for improving productivity in services. In turn, Casado (2005) states that "*many service organizations deal with demands that vary significantly from hour-to-hour and day-to-day. If these organizations cannot satisfy demand as it occurs, they may incur lost sales or other shortage costs. Similarly, if their service capacity exceeds the current rate of demand, the excess capacity may go to waste*". As well, for Van den Bergh et al. (2013), "*the labor cost is the major direct cost component for many companies. Cutting this cost by only a few percent by implementing a new personnel schedule could prove very beneficial*". Zeng et al. (2016) say that since the labor cost is often the significant operating cost in the service industry, utilizing human resources more effectively is highly attractive.

Besides, Morton and Popova (2004) state that researchers hardly ever take into account the unpredictable presence of workers due to illness, arrival delay, or the loss of capacity caused by a resource that is out of service, when scheduling employees. Classical optimization techniques can improve the quality of a scheduling problem but lacks the achievement of solutions that need a fast reaction to condition changes, which are crucial to maintaining the system in operation. Chiaramonte (2016) recognizes that disruptions can occur, which means any event can cause employees or required assets to be unavailable during their scheduled times, needing real-time actions to solve such unexpected situations. The trail of the new millennium has experimented with huge leaps among technology and innovation, one of them in the field of informatics with the implementation of agents to represent with more precision entities and behaviors from a dynamic context. Owing to the inherently dynamic nature of the airports and the lack of efficacy of different electronic programming mechanisms, the recent investigation found in the literature has identified the possibility of implementing software agents to solve the problem of scheduling and improve the quality of the solutions.

Barbati (2012) states that very often, agent-based approaches are used to solve complex problems for which there are no classical optimization techniques available. Also, Van den Bergh et al. (2013) states that most studies appear to feature deterministic approaches, while real-world workforce-scheduling problems must deal with a variety of uncertainty sources. Therefore, these statements show that in a reactive and non-deterministic environment where uncertainty has a strong effect on the personnel schedule, such as volatile demand, last-minute changes, or problems with transportation, it could prove very beneficial to incorporate this uncertainty in the decision-making process. For this reason, agents are a natural option because they can represent a distributed environment and can adjust continually to different responses. Additionally, agents could represent restrictions and employee personal preferences of the modeled entity.

Agent-Based Modelling (ABM) platforms are tools that allow the modeling, simulation, and interactions of complex adaptive systems by using agents, providing a way to simulate results graphically according to several designed scenarios (Alves, 2018). Also, according to Davidsson et al. (2007), the literature seems to confirm that agent-based computing can provide some advantages in terms of computational times, thanks to its ability to divide problems into sub-problems, and to be preferable when the size of the problem is large and its structure domain changes frequently.

Finally, multi-agent systems have found wide application to address complex and dynamic environments related to scheduling problems (Ouelhadj and Petrovic, 2008). Through ABMs it is possible to implement an environment that involves forecasting and exploration of future scenarios, experimenting possible alternative decisions, setting different values for the decision variables, and analyzing the effects of those changes (Axelrod, 1997). Multi-agent systems offer an alternative way to control, analyze, and design systems due to their capability to adapt to changes or disruptions without external intervention. Consequently, the central question of this project is *How to design a multi-agent system to solve the workforce scheduling and transportation problem for an airline company?*

2. Literature review

In related literature, there have been many approaches to solve the workforce-scheduling problem. This section is divided into two parts: Classical or centralized approaches and the agent-based or distributed approaches. Classical centralized approaches are reported to define those aspects and constraints that have been used to model the workforce-scheduling problem. Moreover, classical heuristics have complementary characteristics to agent-based models (ABM) as claimed by Barbati et al. (2012).

First of all, according to Maenhout et al. (2010) and Casado et al. (2005), crew scheduling in the airline context is the process of assigning the necessary crewmembers, in such a way that the airline can operate all its flights and constructing a roster line for each employee, minimizing the corresponding overall cost for personnel. Also, these authors state that the most effective conventional methods for labor scheduling are combined linear programming and local search heuristics. Thus, both studies approach the scheduling problem by presenting a scatter search algorithm, deciding if extra personnel should be employed. As a consequence, the objective is to assign a personalized roster to each crewmember minimizing the overall operational costs while ensuring the social quality of the schedule by considering the crewmembers' preferences, such as days and hours in which the employee wants or can work, or take into account the activities/tasks that some employees want or don't want to do. The performance of the algorithm in both cases showed efficient results with small computational effort, critical for solving crew-scheduling problems rapidly daily, even with problems of realistic sizes, which involve many shifts and long-term planning horizons.

Also, in their article "A Rolling Horizon Solution Approach for the Airline Crew Pairing Problem", Saddoune, Desaulniers and Soumis (2009) tackled the crew pairing problem (CPP), a step in the airline crew scheduling process, consisting in determining a minimum cost set of feasible pairings (crew rotations) such that each flight is covered precisely once and constraints are feasible. According to the authors, the problem is usually solved by a three-phase heuristic that solves a daily, weekly and monthly scheduling sequentially. The primary purpose of their study is to propose a rolling horizon approach (RH) because the traditional approach is less efficient in solving the crew problem, given that flight schedules are not regular. The method is based on column generation, where the solution process is separated into two stages: pairing generation and pairing selection, but it solves the monthly problem, skipping the first two phases. Dück et al. (2012) uses a similar approach based on column generations to deal with stability in the planning of workforce scheduling and proposes robust scheduling for minimizing the operational costs by constructing the schedules in the planning phase in such a way that possible daily disruptions are considered.

Zeng et al. (2016) state that airport ground staff scheduling is intricate since the demand for ground service, for instance, check-in, boarding, help desks, and ramp operations, substantially varies throughout the day. However, in contrast to the abundant literature on crew scheduling, little attention has been focused, on-ground staff. They address the problem of workforce planning for airport staff with a branch-and-price approach to find a minimum workforce mix that satisfies a given demand profile. The authors propose a new formulation to the given approach by using hierarchical skills in which staff with higher-level skills is permitted to cover demands of lower levels. This approach was compared to different heuristics implemented in previous works and the results showed advantages to the proposed model and produced near-optimal solutions. Stoletz (2010) proposed a binary linear programming approach to tackle the workforce planning problem in check-in counters at airports to assign agents to tours, i.e., to shifts and days-off over a planning horizon. Also, to optimize the scheduling, the author presented a reduced set-covering formulation that considered individual employee preferences.

On the other hand, agent-based models (ABM) have been recently applied to solve optimization problems that present several interrelated components in a distributed and heterogeneous environment. ABMs can be useful to reproduce many systems related to economics and social sciences, where the structure can be designed through a network (Billari et al., 1997). In their literature review, Barbati et al. (2012) identified ABM applications and gathered several studies that primarily focused on the use of those models to solve optimization problems. Considering the applications, ABMs seem to be particularly suitable to tackle scheduling problems, followed by transportation and logistics problems. The results of the survey reveal that ABM approaches are successfully employed to solve numerous optimization problems, especially complex scheduling problems. Zhao and DeLaurentis (2008) mentioned opportunities for agent-based modeling in air transportation and claims that agent-based modeling has found productive in this domain by providing flexible tools for analysis of large-scale interacting systems. However, a hybrid system that combines the advantages of both agents and other optimization tools like heuristics in which agents can learn from experiences and adjust their behavior accordingly is the desired approach.

Yousefi and Ferreira (2017) state that for complex and dynamic systems such as the ones involving workforce-scheduling, there is not a standard model to help organize the performance of the system and managers frequently use trial and error methods which can lead to high risks in the organization. For instance, in the field of health & care and nurse scheduling, selecting a key performance indicator (KPI) is a controversial issue. Although there is not a general rule for selecting a KPI, the most used in this field is the number of patients leaving the emergency department without proper care, the number of patients discharged, the length of stay, the time to see a doctor, and average waiting times. Nowadays, three main simulation approaches are widely applied: Discrete event simulation, agent-based simulation, and system dynamics. Although discrete event simulation is the preferred method, recent reviews show that the use of agent-based simulation (ABS) has increased, making ABS a more reliable tool, mainly because of its interactive decision-making skills, in which agents interact with each other and with the environment so they can evolve. In ABS, agents react to different situations in the system and, thus, improve the performance of the solution. Günther and Nissen (2010) compare a centralized Particle Swarm Optimization (PSO) with a decentralized approach involving agents who negotiate to construct a staff schedule. Even though both approaches significantly outperform manual planning, the agent solution is quicker in finding solutions of almost the same quality as PSO, and the results suggest that agents could be an interesting method for real-time scheduling or re-scheduling tasks.

Wang et al. (2009) propose a multi-agent system focusing on scheduling based on preferences. The idea is to consider the individual preferences of nurses when generating schedules, creating a new concept called preference points. Preference points are used to quantify the value on each preference, so that nurses can indicate their preferences before the beginning of the planning horizon. By doing so, it is possible to configure the profiles of agents so that agents collectively build these schedules by negotiating with each other.

In their article "Re-rostering of nurses with intelligent agents and iterated local search", Chiaramonte and Caswell (2016) tackle the re-rostering problem. This alteration occurs when an interruption in a current list of employees requires reconstruction. The authors present an agent-based system called Competitive Nurse Rostering-Rerostering (CNRR) that solves both the problem of workforce-scheduling and re-rostering, minimizing the difference between the initial list and the reconstructed list and minimizing the negative impact on the preferences of the nurses, using negotiations and the concept of iterated local search. This approach is accomplished by exchanging one-to-one shifts and determining which shift trades can be made via preference analysis. The agent-based system tested various experiments and found solutions for more than 90% of the tests. The generated solutions avoided any reduction in the satisfaction of nursing preferences in more than half of the experiments, which is vital to help reduce employee dissatisfaction and improve retention. Similarly, in the context of a multi-product assembly center, Sabar and Frayret (2012) proposed an agent-based algorithm for the rostering/re-rostering of personnel, minimizing both the operational costs and personnel dissatisfactions, and taking into account individual competencies, mobility, preferences, and requirements associated with activities. The system was based on the cooperation between agents that encapsulated individual competencies and employee preferences. In this approach, agents negotiate to form coalitions, which allow them to improve their schedules and, consequently, improve the solution. Compared to a standard simulation, the model obtained a much higher quality solution with minimal computational effort.

According to Castillo et al. (2016), in the context of workforce scheduling, in various scenarios, personnel must carry out tasks at different locations requiring transportation. These scenarios are referred to as Workforce Scheduling and Routing Problems (WSRP) as they usually involve the scheduling of personnel combined with some form of routing to ensure that employees arrive on time to the locations where tasks need to be performed. Alves et al. (2018), in an attempt to improve operational management problems related to the programming and optimization of human and material resources, took advantage of the characteristics of multi-agent systems to present a methodology that minimizes travel times in vehicle routes during home visits, characterized by the dynamic context with uncertainties and random events. The proposal combines the optimization features provided by centralized programming algorithms, e.g., genetic algorithms, with the responsive characteristics provided by multi-agent systems solutions. A first module performs the optimized programming for vehicle routes, and the second performs the dynamic reprogramming, which is responsible for responding to interruptions or changes in conditions. The vehicle follows the planned route but can dynamically adapt the schedule in case of interruptions through interaction with other vehicles to redirect the previously assigned visits. Also, Shibghatullah et al. (2010) model the crew bus scheduling process using agents and simulate its behavior to establish ways of automating the management of unpredictable events so that it can assist supervisors in reassigning crews if needed. The authors used the Gaia methodology, which deals with internal aspects of agent and interaction in a system, providing a basic notation in the design of interaction and communication between agents.

Štiglic and Kokol (2006) present another approach to the problem of nurse programming. In their article "Intelligent programming of patients and nurses in ambulatory health care centers" with the main objective of reducing average waiting times and maintaining a high use of resources, they combine multi-agent systems with time series forecasts, where agents use their prediction and pattern recognition capabilities to predict possible spikes in patient flows and inform these events. By doing so, it is possible to adapt the programming of nurses and patients based on the current flow of patients. This kind of artificial intelligence in agents is useful when there are constant patterns in a patient flow that can be difficult to spot for a workforce manager. The task of each agent is to forecast the patient flow volume shortly and inform the patient/nurse scheduler of the forecasted patient flow changes. To compare the adaptive method of multi-agent systems and time series pattern recognition, the authors simulated it with the non-adaptive method First Come First Served (FCFS).

Kanaga, Darius, and Valarmathi (2009) in need of efficient management of resources and better treatment for the patients implemented a multi-agent system to solve the patient scheduling problem with the use of a combinatorial auction. A combinatorial auction is a specialized form of market-based coordination mechanism used to coordinate the allocation of time slots of the resource. The model has three main agents: The Resource Agent (RA), the Patient Agent (PA), and the Common Agent (CA). The combinatorial auction consists of bids for multiple time slots from various resources between the PA and RA in which each resource agent is an auctioneer, and each patient agent is a bidder. The objective of the auction is to minimize the overall weighted waiting time for the patients. The result is an optimized schedule for each patient and resource. The performance of the proposed system is evaluated against the performance of traditional scheduling algorithms, such as FCFS. The proposed framework had the least weighted waiting time value in comparison with the other algorithms, showing that the auction-based model is more effective in dynamic and decentralized environments.

This project will address the problem with a list of features that are not usually treated together in the literature. Most of the previous studies have various contexts to perform workforce scheduling. Thus, they will serve as the basis for this project because the implementation of multi-agent systems can cover several domains of study. In the personnel scheduling, factors such as preferences, skills, and restrictions that are the main focus in health & care contexts, can also be applied to the airline workforce environment with the addition of both the workforce-scheduling programming and personnel transportation. Therefore, the primary purpose of the project is to integrate the workforce-scheduling with the transportation of employees to/from work, taking into account considerations established by the airline.

3. Objectives

This project looks to answer the following research question: *How to design a multi-agent system to solve the workforce scheduling and transportation problem (WOSTRA) for an airline company*? Therefore, the main objective is to design and implement in a software an agent-based model that solves the workforce scheduling of the airline company and integrates such schedule with the transportation decisions that allow the personnel to arrive on time at the airport, as well as returning personnel to their households. This main objective will be achieved by accomplishing the following specific objectives:

- Explore the different agent-based paradigms and choose one for the airline workforce scheduling and personnel transportation problem.
- Design an agent-based model for the workforce scheduling and personnel transportation problem.
- Implement the proposed agent-based model using agent-based simulation software.
- Validate and evaluate, through various scenarios, the proposed approach and report results based on performance indicators for a specific case study.

3.1. Design Statement

This project focuses on the design of an agent-based simulation model and its implementation that allows workforce scheduling and personnel transportation.

3.2. Design requirements

The proposed model must accomplish the following requirements:

- The implementation of the simulation model must obtain feasible solutions to the workforce-scheduling problem, including the transportation of employees while fulfilling all the constraints established by the airline such as different activities that employees can do, duration of shifts, restrictions on shifts, definitions and restrictions regarding transportation and the well-being of the employees.
- The implementation of the simulation model must be able to adapt to different scenarios, such as different periods of the year, and unexpected changes where passenger demand in the airports may vary.
- The implementation of the simulation model must allow changing inputs and parameters if needed.
- The implementation of the simulation model must report a performance indicator for evaluating the impact of the solution.

3.3. Design restrictions

- The simulation of scenarios and results will depend on the information collected from the airline. The closer to reality the gathered data is, the better the results.
- If the information is limited, the scenarios will be based on theoretical data that will be used for validation.
- The implementation of the simulation model must find a solution in a period between 15 and 25 minutes to ensure reactivity.
- The implementation of the simulation model must offer a schedule for a working week of 7 days.
- The maximum number of agents of the airline to be scheduled and transported during the simulation will be 75 agents.

3.4. Norms and standards

The methodology that will be used in this project is described by the ISO 13053-1 for the quantitative methods in process improvement. This methodology typically comprises five phases: Define, Measure, Analyze, Improve, and Control (“ISO 13053-1, Quantitative methods in process improvement — Six Sigma — Part 1: DMAIC methodology,” 2011).

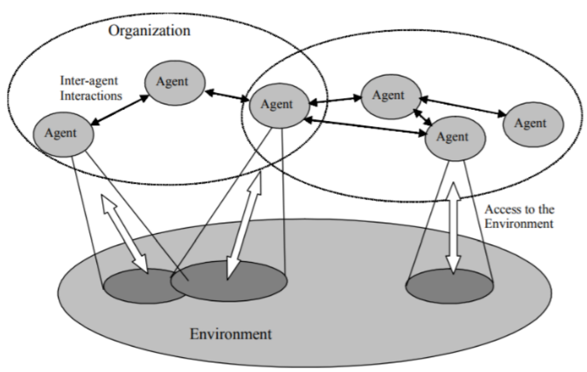
4. Proposed Methodology

4.1. Specific objective 1

The resolution of this first objective is directly related to the first phase of the DMAIC methodology, aiming to define the agent-based paradigm appropriate to solve the problem. The approach focuses on the development of a medium to large size system, possibly situated in open and dynamic environments, that must guarantee predictable and reliable behaviors. For these kinds of systems, the most appropriate methodology is the organizational approach.

The organizational perspective leads to a general architectural characterization of a Multi-Agent System (MAS) as depicted in *Figure 2*, in which a MAS can be abstracted as a set of interacting sub-organizations with a subset of the agents possibly belonging to multiple organizations. In each organization, agents can play one or more roles and interact with each other to exchange knowledge and coordinate their activities. Besides, the MAS is typically immersed in an environment in which agents interact via various kinds of sensors.

Figure 2. Multiagent systems as computational organizations [Jennings, 2000].



Gaia is the methodology that will be implemented to solve the problem at hand. The Gaia methodology will be compared with other agent-oriented methodologies to illustrate why this methodology was used instead of others. It is crucial to keep in mind that the best methodology for this research depends on the objective application since each application leads to a different set of requirements, which may have different evaluation criteria.

The evaluation and comparison are conducted using the feature analysis approach used in Jennings (2000). The authors used a variation of said approach. Feature analysis is the most common and cost-effective approach compared to other evaluation techniques. The characteristic analysis uses a checklist of evaluation criteria to evaluate and compare methodologies based on selected characteristics.

For the comparison, criteria related to the process and the model characteristics will be considered, since these criteria cover the main components of a methodology for the development of systems.

- **Process criteria**: Applicability of the methodology. The planned steps for the development process and the development approach followed by the methodology.

Table 1. MAS methodologies process criteria comparison

Process Criteria	Gaia	MaSE	MAS-Common KADS	Ingenias	Prometheus	Tropos	Passi
Size of MAS	100 agents	10 agents	Not specified	Not specified	Any	Not specified	Not specified
Ease of following the process steps	High	High	Medium	High	Medium	High	Medium

As seen in *Table 1*, the Gaia methodology supports up to 100 agents in their environments, allowing us to solve the scheduling problem in the airline easily and making methodologies like MaSE and others non-viable and unable to fill the capacity level of the required number of agents.

- **Model criteria**: Evaluate the various aspects of the notation models and components of a methodology, including the concepts represented by the models, the quality of the notation components, and the agent characteristics supported by the models.

Table 2. MAS methodologies model criteria comparison

Model Criteria	Gaia	MaSE	MAS-Common KADS	Ingenias	Prometheus	Tropos	Passi
Expressiveness	Medium	High	High	High	High	High	High
Modularity	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Autonomy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adaptability	Yes	No	No	No	No	No	No
Cooperative behavior	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reactivity	Yes	Yes	Yes	Yes	Yes	Yes	Yes

As seen in *Table 2*, the seven methodologies in comparison are very similar in the model criteria, except for the adaptability criterion, in which only Gaia applies it, making Gaia a better candidate to tackle the problem at hand. Also, various reasons have been found in the literature that favors Gaia to achieve the objectives of this project.

According to Sánchez-Pi, Carbó, and Molina (2010), methodologies such as MaSE, MAS Common-KADS, and Ingenias could be used to analyze a problem such as the personnel scheduling in an airport context, but these methodologies have characteristics that make the process more complex since these methodologies use object-oriented techniques and specification languages and the main intention of the problem is to only focus on the organizational abstractions as mentioned above. Cernuzzi et al. (2011) discuss that whenever methodologies do not prescribe the explicit modeling of the organizational structure of the Multi-Agent system, accommodating their likely changes might be difficult.

In addition, Cernuzzi and Zambonelli (2005) says that unlike Gaia, several other MAS methodologies proposed in the literature simply miss in identifying a clear separation of the intrinsic aspects of a Multi-agent system from the architectural aspects (i.e., the organizational structure). Zambonelli, et al. (2003) back up these affirmations by saying that methodologies like MaSE, Prometheus and Tropos fail to identify any organizational abstraction and does not explicitly identify the concept of organizational rules and neither of these methodologies can capture global laws that apply to multiple organizational roles or the organization as a whole.

Last, Cernuzzi and Zambonelli (2005) also state that Gaia models both the macro (social) aspect and the micro (agent internals) aspect of a MAS, and devotes a specific effort to model the organizational structure and the organizational rules that govern the global behavior of the agents in the organization and also to capture the characteristics of the agents such as being proactive, reactive and having social capabilities. Gaia allows moving from abstract concepts to increasingly concrete concepts. Abstract concepts are those that are used during the analysis phase to conceptualize the system as roles, responsibilities, protocols, activities, vitality and security. The concrete concepts have to do with the design process as execution time and the interactions between agents.

Gaia is founded on the view of a multi-agent system as a computational organization consisting of various interacting roles. Wooldridge et al. (2000) state that Gaia encourages a developer to think of building agent-based systems as a process of organizational design with characteristics such as:

- **Precision**: The properties of vitality and security in the definition of roles make the model accurate and avoid misunderstandings in the functionalities.
- **Accessibility**: The easiness of understanding and use due to its simple models and clarity in the model's construction.
- **Expressive**: Gaia can handle a wide variety of systems because it has a generic structure.
- **Modularity**: Gaia is modular due to its basic components, such as roles, protocols, and activities.

In conclusion, Gaia specifies how a society of agents collaborates to achieve the objectives of the system and the contribution of each agent, facilitating the tackling of likely changes that will appear in a MAS with more ease, and this is precisely what is needed for the solution of the problem at hand.

4.2. Specific objective 2

The resolution of this second objective is also directly related to the first phase of the DMAIC methodology, aiming to define the MAS system using the GAIA methodology. The Gaia methodology includes two main phases: the analysis phase and the design phase. The Gaia process starts with the analysis phase, whose main goal is the collection and organization of the system's specification, which is the basis for the design of the computational organization. This phase includes the definition of organizational rules, the environment model, the role model, and the interaction model.

- **Organizational Rules**

The organizational rules identify a set of organizational rules and norms, expressing global constraints/directives that govern the multi-agent system behavior. It is essential to understand what kind of indicators and restrictions the system must have because it helps identify agents, their requirements, behaviors, and characteristics to accomplish the objective of the organization. Those indicators have been done by the professor Mohamed Rabie NaitAbdallah for the class "Optimización de Operaciones" at Javeriana University for the development of the Challenge Latam Javeriana 2019-10 that is described at reported *4.2.1 Problem Description.*

Table 3. Liveness Restrictions.

Restriction	Description
Hours per worker	Each worker must have nine hours per shift
Pauses during shifts	Each worker must have a one-hour break during the shift. Each break depends on the time the agent enters the shift.
Number of agents	A maximum of 75 agents can be assigned
Rest between shifts	Each worker must rest 12 hours between shifts

Free days	Each worker must have at least one day of rest during the week
Transport assignation	Depending on the hours of entry or exit of the shifts, the agents will have to be assigned vehicles for transportation.

Also, in an airline context, different unexpected scenarios are resolved at the moment that they occur. Those usually are solved by the supervisors or by workers depending on the situation. For this reason, this project will develop two hypothetical scenarios, because the organization does not possess sufficient data to propose real scenarios.

The first scenario is an unexpected peak of demand of any given activity during any shift because the data input of passengers demand to decide the schedule of agents is constructed on estimations and it could fail; consequently, it is resolved by the organizational rules taking into account liveness restrictions in *Table 3*.

The second scenario is the absence of workers; in this scenario it is assumed that the worker that will be absent reports early to the supervisor the absence. Consequently, the organization seeks a worker that could supply this absence, considering the liveness restrictions described in *Table 3*.

- **Environmental model**

Since the importance of environments, because a multi-agent system is always situated in some domain, modeling this environment involves determining which entities and resources take part of the MAS, for reaching the organizational goal. In this application example, the environmental mode mostly reduces to a virtual computational environment made of personnel scheduling and transportation routing for an airline company.

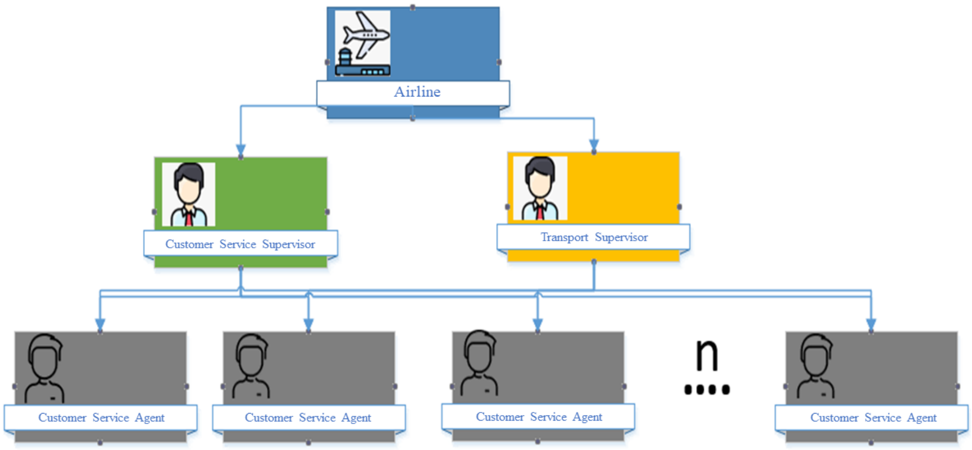
- **Role model**

A role model identifies the main roles that agents can play in the system. A role is viewed as a description of the functionality of an agent, and it includes four attributes: permissions (resources use while performing a role), responsibilities (expected behaviors of the role), activities (actions without interaction between roles) and protocols (actions than involve interaction between roles). The following roles have been defined in the proposed multi-agent system:

- ✓ **Airline Agent (AA)**: This role represents the organization where there are different events, requirements, and information about its payroll in addition to the needs that the company must satisfy.
- ✓ **Human resources/Customer Service Supervisor (CSS)**: This role is responsible for ensuring that the company's requirements are met, ensuring the well-being of customer service agents. Assigns the activities for customer service agents, starting hour per shift and reports the results obtained.
- ✓ **Transport Supervisor (TS)**: This role evaluates and generates transport leaders for each shift that requires transportation, so it facilitates the arrangement of vehicles.
- ✓ **Customer Service Agents (CSA):** Customer service staff establish their abilities and the possible order they could perform during the week; also, they interact to determine the vehicles and order of a route.

In *Figure 3*, the hierarchy and the roles are shown, to describe how the communication will work in the multi-agent system.

Figure 3. Hierarchy and roles of the airline.



The roles of the Airline System are described in reported *4.2.2 Role Model*, according to Gaia's specifications. As well, the actors, which are the basis for the roles of the model, are described in reported *4.2.3 Actors.*

- **Interaction model**

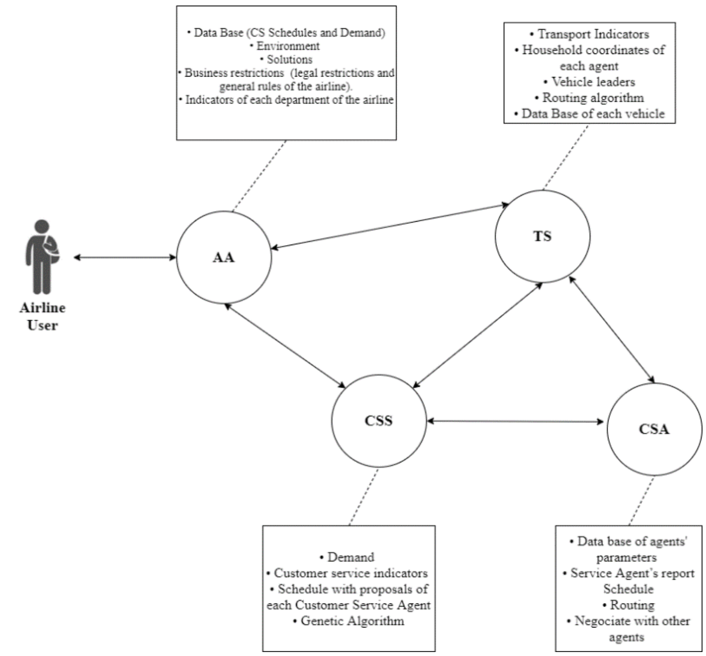
There are inevitably dependencies and relationships between the various roles in a multi-agent organization. An interaction model is used to represent these dependencies and relationships between roles, according to protocol definitions. This model consists of a set of protocol definitions, one for each type of inter-role interaction. For the roles, eleven protocols are defined in reported *4.2.4 Interaction Protocols*. Also, reported *4.2.5 Schedule Airline MAS-BPMN* shows a BPMN diagram shows the expected interactions between agents in the proposed system.

The design phase exploits the output of the analysis phase. This phase includes two models: The agent and the service models. These phases help to identify, respectively, the agent types in the system and the main services that are required to realize the agent's role.

- **Agent model**

The purpose of the Gaia agent model is to document the various agent types that are used in the system under development. These agent instances will realize these agent types at run-time, interactions between them, and data input and outputs of these agent types. This model is detailed, as follows in *Figure 4*.

Figure 4. Agent model.



- **Service model**

The service model in the Gaia methodology represents all protocols, activities, responsibilities, and liveness, associated with the roles that agents play in the system. This model is shown with more detail in reported *4.2.6 Service Model*.

4.3. Specific objective 3

4.3.1. JADE Platform

As seen in the previous section, Gaia has been proposed as the methodology to tackle the problem. However, it covers only the requirements, analysis, and design phases of the development cycle. For this reason, it is necessary to have practical tools for allowing the analysis and design phases of the methodology to be implemented.

According to Moraitis and Spanoudakis (2004), the Gaia methodology was considered as quite easy to learn and use to analyze and design a multiagent system. It proved to be robust, reliable, and the resulting models were used throughout the development phases as a reference. Moreover, it proved to be flexible enough so that it was easy to iterate through the design and implementation phases.

Research in MAS has recently led to the development of practical programming languages and tools that are appropriate for the implementation of systems. Using these languages and platforms, instead of more conventional ones, proves to be useful when the problem is modeled as a MAS, and understood in terms of cognitive and social concepts such as beliefs, goals, plans, roles, and norms.

Bordini et al. (2006) state that JADE is a software framework to facilitate the development of multi-agent applications. It represents an agent middleware providing a set of available and easy-to-use services and several graphical tools for debugging and testing, in addition, the agent platform can be distributed across multiple machines, regardless of the underlying operating system. Bellifemine et al. (2000) also states that JADE is very flexible and can be adapted to be used on devices with limited resources. Currently, the most popular solution is to use JADE as an underlying agent infrastructure to program the agents' behavior. It is the software that will be used to implement the system.

A class diagram was made to show the relationships and structure of the system implementation following the GAIA roles described previously in which each main class represents the role of the airline. As well, each class has its attributes (Characteristics) and operations (Behaviors). According to Nikraz et al. (2006), the actual job an agent must do is typically carried out within the agent's behaviors. Hence, the system should look at the agent responsibilities and activities identified in the analysis phase of GAIA and map them to agent behaviors, whether it is a Cyclic Behavior (a task that is always active and performs the same operations each time it is scheduled) or a One-Shot Behavior (a task that runs once and terminates immediately). The main entities of the system and how they are implemented are the following:

- **Airline Agent**

Besides of what's mentioned in the role model, this entity is responsible for instantiating or initializing the 75 agents of the customer service and sending their data like restrictions to carry out activities (defined as A, B, C) and restrictions on the days off that the agent needs to meet for the one-week planning horizon.

The entity, being instantiated, creates a Cyclic Behavior called the *best schedule* where it waits for the message of the CSS with the best genetic algorithm solution regarding the issue of scheduling agents at the airport. Once the AA gets the best scheduling solution, a One-Shot Behavior is instantiated called *request Routing*, where the airline communicates with the TS and sends it the best workforce schedule for the supervisor to carry out the transport and routing of the agents.

- **Customer Service Supervisor**

This entity is responsible for scheduling the agents, based on a genetic algorithm. Before performing the algorithm to obtain a solution to the problem, this entity oversees initializing the passenger demand data for each activity, as well as managing the work breaks depending on the entry time of each agent. With this data, a behavior called *genetic algorithm* is created. The genetic algorithm for the CSS will be defined (Data structures and heuristics) with its parameters (Reproduction, mutation, generations) in the next section of the document.

Once the genetic algorithm is finished with its execution and a feasible solution is found, the supervisor communicates with the airline and sends the solution which contains the scheduling of each agent for the one-week planning horizon, showing start times and activities to be carried out in each band for each day, and the objective function (OF) of the scheduling part.

- **Transport Supervisor**

This entity is responsible for transportation of the CSA from the airport to their homes and from their homes to the airport, considering certain time restrictions. This entity initializes the data of the house coordinates of each agent and the distances between each pair of agents and between each agent and the airport.

This supervisor also creates a Cyclic Behavior called the *routing agent* and another behavior called *routing*. The first is a behavior that will remain on hold until the airline communicates with it and gives it the workforce schedule in order to define which agents are going to need transportation (either back or forth) and at what time they will need it.

Once the supervisor has determined which service agents need transportation along the planning horizon, the second behavior starts. This behavior determines the leaders of the vehicles to be assigned for each day and hour. Once the leaders are created, the agents begin to communicate with each other and perform the transport clusters. Once all clusters are assigned, the routes and vehicles with the agents are created by the supervisor and the value of the OF of the transport part is calculated. When the OF is calculated and the routes and vehicles are ready, the supervisor communicates again with the airline agent by sending the routes and vehicles and the value of the OF.

- **Customer Service Agent**

Also, of what is mentioned in the role model, this entity oversees the communication with the cluster leaders and reports to any of the corresponding cluster leaders if they will go with them in the vehicle considering the distances between them.

The class diagram for the implementation of the system is represented in reported *4.3.1 Class Diagram*.

4.3.2. Decision-making process

Besides the aforementioned agents and their relationship with the design phase of GAIA, there are implementations of each agent that facilitate the decision-making process of those agents. For this reason, each agent has its behaviors and a Graphical User Interface (GUI) to visualize the result of their decisions.

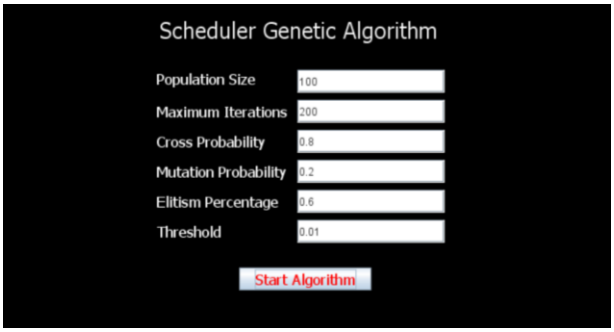
4.3.2.1. Scheduling decision-making

There are two interfaces to interact with the CSS, the first is to enter the parameters needed by the Genetic Algorithm (GA). The parameters are described as follows:

- Population size (PS): The number of chromosomes that are going to be instantiated for the solution.
- Maximum Iterations (MI): The number of iterations without improvement in the objective function that the GA will have to do before finishing.
- Crossover Probability (CP): The ratio of next generation population born by crossover operation.
- Mutation Probability (MP): The probability that a chromosome is affected or altered.
- Elitism Percentage (EP): The percentage of chromosomes from the past generation that has a 100% probability of being in the new generation.
- Threshold (TH): Threshold that the best chromosome of the current generation has to meet for iterations to restart.

Before explaining the steps that were carried out to build the genetic algorithm, the two interfaces that the system has implemented are shown. *Figure 5* represents the interface that is displayed to the user once the program is running. It shows all the data that the GA needs to start with the solution of the workforce scheduling. The CP, MP, EP and TH fields in the GUI are probabilities, meaning the user must insert numbers between [0, 1] in each of the respective fields.

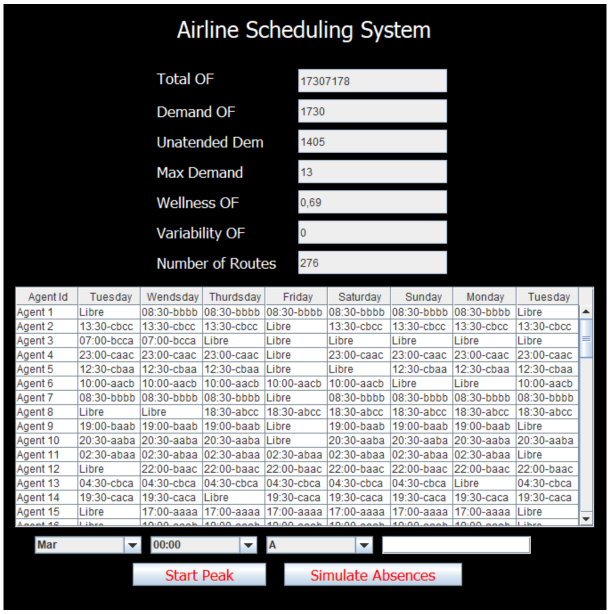
Figure 5. GUI for the genetic algorithm initialization.



Once the "Start Algorithm" button is pressed, the CSS starts performing the GA. Once finished and the best solution or chromosome is found, this solution is reported to the airline agent. The airline agent then sends it to the transport supervisor. *Figure 6* shows the results of the scheduling of airline personnel with their respective schedules and the respective objective function. A table is shown with the final schedule for the weekly planning horizon. The table shows the respective schedule for each of the customer service agents that are working during the week. It displays the starting hour of the shift for each working day, which days the agent is at rest, and the activities the agent must do for each of the four timeslots for each day. 5 fields are displayed in total:

- Total OF: Indicates the value of the total objective function used by the airline, considering the scheduling part and the routing part.
- Unattended OF: Indicates the value of the objective function of the scheduling part, and more precisely, the demand satisfaction.
- Wellness OF: Indicates the value of the objective function of the routing part, and more precisely, the welfare of the agents when carrying out the transportation to the airport and back.
- Variability OF: Indicates the value of the objective function of the scheduling part, and more precisely, the time variability in the starting times of the daily shifts for each service agent.
- Number of routes: Indicates the value of the objective function of the routing part, and more precisely, the total number of routes that the airline has to carry out to transport the service agents from their households to the airport and from the airport to their households.

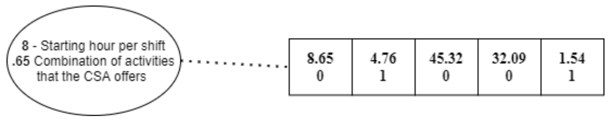
Figure 6. GUI for the results of the personnel scheduling of agents.



4.3.2.1.1. Genetic Algorithm

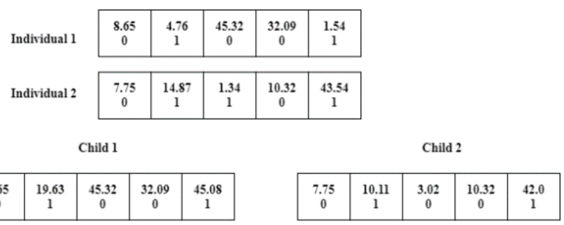
For the representation of an individual chromosome, *Figure 7*, is used inside the GA. The chromosome is implemented by a vector of ***n*** positions (each position represents a CSA). Each of the ***n*** positions is encoded with a random decimal number between 0 and 47 (Representing the 48 timeslots of a day). This indirect codification developed by the authors, represents an integer number, of the starting hour of shifts during the week and the remaining decimal number (with two decimal positions) represents an index in the list of activities that the CSA has to attend in the four timeslots of each shift. This list of activities is a list that each CSA has with all the possible 4-combinations (Each shift has four timeslots) of activities that the agent can do. As well, each position is given a random number which can only be 0 or 1. This number will represent the genome of that particular agent for the respective chromosome.

Figure 7. Chromosome indirect encoding



Furthermore, the crossover is done by determining the encoding mask of genomes of each father. First, the generation of the first child is completed by analyzing the genomes of the first father; if the genome is 0 it is inherited directly to the child, if not, the number is added with the genome of the other father. To generate the second child the process is similar but instead of adding the numbers, they are subtracted. Since the adding or subtracting of the possible timeslots for the new child's are guaranteed to be in the range [-47, 47], if the subtraction of the two fathers is negative, then the final number is 47 minus that number. This is done so that every number generated is in the range [0, 47] and it is easier to establish the starting hour for each shift. This process is represented in *Figure 8*.

Figure 8. Crossover representation.



Afterward, the mutation process is realized with each generated child, selecting a random position where the chromosome is cut and swapped with the rest of it. Finally, elitism is applied partially, to preserve part of the population that does not have the best performance.

Finally, the performance is calculated with the Fitness, for this reason, those chromosomes are ranked in ascending order because the objective of the algorithm is to minimize the objective function of human resources which focus on minimize the quantity of activities unattended also the maximum number of activities per period. The Equation 1 illustrated the calculous of Fitness.

Equation 1. Fitness and Objective Function of Human Resources.

$$Fitness = \frac{1}{OFUnattended}$$

$$OFUnattended = \sum_{d=1}^{7} \sum_{p=0}^{23} Un_{d,p} + 25 * max_{\substack{d=1...7 \\ p=0....23}} (Un_{d,p})$$

$$Un_{d,p} = Max(0, Dem_{d,p,h} - N_{d,p,h})$$

$Un_{d,p}$: The number of agents missing to satisfy the total demand in period p on day d.

$Dem_{d,p}$: The demand of agents required in period p on day d.

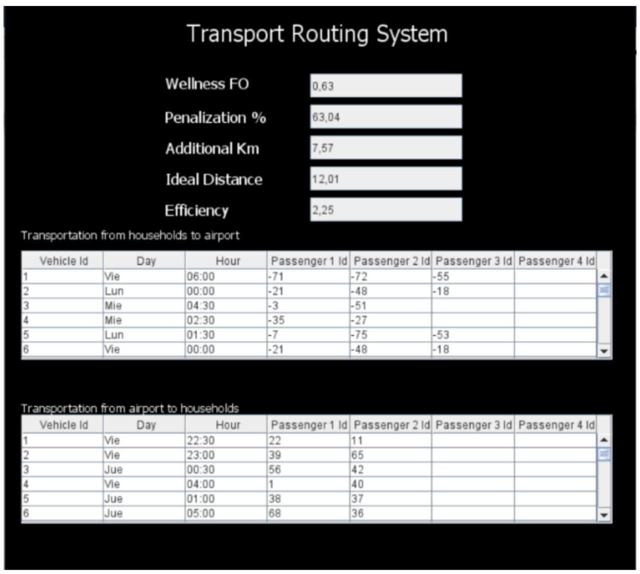
$N_{d,p,h}$: The number of agents assigned to attend the demand of the activity h during the period p on day d.

4.3.2.2. Routing and transportation decision-making

The routing process starts when the TS agent determinates all the CSA that needs transportation, then this agent generates leaders depending on the position of the CSA for each timeslot. The CSA that are not leaders will be referred as non-leaders.

Eventually, those leaders and non-leaders initiate a Contract-Net or negotiation protocol where each leader proposes to be part of his/her vehicle, and the non-leader choose who is the best option for his/her local indicator (closeness). Finally, the leader with the agents they have accepted generates the best route using the heuristic Nearest Neighbor and reports the travelers and the route to the TS.

Figure 9. GUI for the results of the transportation and routing of agents.



Once the GA for the personnel scheduling and routing algorithm is completed, both solutions are reported to the airline agent, and the airline agent oversees visualizing the results. *Figure 9* shows the results of the routing of airline personnel with their respective routes and vehicles. A table is shown with the result of the routing and the assignment of vehicles, where the vehicles to which each agent belongs are shown, both going (Houses - Airport) and back (Airport - Houses). For each vehicle, the day and time on which the vehicle starts its route and the agents (Between 1 and 4) that belong to that vehicle are indicated. 5 fields are displayed in total:

- Wellness OF: It indicates the value of the objective function of the routing part and more precisely, the welfare part of the agents when carrying out the transportation to the airport and back.
- Penalization %: Indicates the percentage of the penalty incurred in passenger transport. This is obtained by dividing the additional Km over the ideal Distance.
- Additional Km: Indicates an average of the additional km of passengers having indirect journeys.
- Ideal Km: Indicates an average of the ideal distance (Km) if all journeys were direct journeys.
- Efficiency: The efficiency indicates how good is the use of vehicles in terms of the number of passengers per vehicle.

Also, it is important to mention the objective function that the transport supervisor calculates according each route that leaders have been done. This is named as Wellness OF that is illustrated on the Equation 2

Equation 2. Wellness equation.

$$OFWelness = \frac{\frac{\sum_{t \in IndRoutes} KmExtraIndirect_t}{NIndirect}}{\frac{\sum_{t \in Routes} IdealKm_t}{N}}$$

$IdealKm_t$: The ideal distance a passenger would have if he/she has a direct route (travel alone in a car).

$KmExtraIndirect_t$: Difference between the actual distance traveled by passenger and the ideal distance if the agent had a direct route.

$NIndirect$: Number of indirect routes.

N: Number of passengers carried.

4.3.3. Perturbation scenarios

As stated in the organizational rules in the analysis phase of the GAIA methodology, in this section, two different perturbations are presented to see the reactivity of the system. The basic operation of the two perturbations is that there is a problem with the airline and that problem is reported to the relevant supervisor agent (CSS or TS), and they report the problem to the CSA. These agents, once they find out what the problem at hand is, will apply to deal with the perturbance, considering internal feasibility issues that each agent must verify before applying (Primarily, those shown in *Table 3*). Finally, each supervisor checks one last time each proposal made by the agents and is the one who finally decides which agent/agents will attend the perturbation in question, with the main consideration of minimizing changes in the objective function.

4.3.3.1. Peak Demand Perturbation

This perturbation focusses on allowing the user to simulate a peak of the demand of any activity because the actual model uses estimations of the demand for each activity. The user has the option to select a day, a period, activity, and the quantity of extra demand to simulate.

The process starts with the CSS detecting the extra demand and asking the CSA if they could attend the demand of that activity. Each agent determines if they are currently working when the peak is presented and if they can attend this activity.

Finally, the CSS, with the proposals sent by the agents, determines which agents are idle during the peak. If none of the agents can attend the peak, a second evaluation is considered, and that is the level of importance each activity has at the moment. The importance of the activity, it is determined by analyzing the unattended demand of the activity during the timeslot of the peak. The CSS, then decides if the change of activity is going to make the *max Demand* indicator in the scheduling objective function better. If it does, then the change is made, if not, the agent will stay in the initial activity.

4.3.3.2. Absences Perturbation

This perturbation focusses on simulating with a discrete uniform variable with lower bound equal to 2 and an upper bound equal to 7, the number of possible agents that could be absent on a given day during the week of planning. The system simulates this issue and reacts to resolve it.

The process starts when the CSS agent detects the CSA that will be absent and asks the other agents if they could work on a free day and how many activities of the timeslots of the absent agent could they attend. Once every agent responds to the CSS, the CSS evaluates all the options taking into primary consideration the minimization of the variability indicator and the maximization of the activities the new agent can attend from the absent agent.

Finally, with those decisions and the new agents already stablished in the new schedule, the transport supervisor determines if the changes made, affects the transportation. If yes, the new agents that are supplying the absents, determines if they could be part of any car as long as they do not affect the *additional kilometers mean* indicator.

4.4. Specific objective 4

This section explains the DMAIC phases corresponding to measure, analyze, and improve. The control phase was not implemented because it requires the actual implementation of this proposal and a feedback from the airline employees to close the design cycle. The three phases presented here are executed on the basis of data provided by the airline.

4.4.1. Measurement tools

With the final purpose to measure the impact, three solutions (Airline solution, VBA, and MAS) were generated using a validator made by the professor Mohamed Rabie NaitAbdallah, which generates indicators of scheduled programming, such as, missing demand, distribution activities and schedule variability. As well, transport indicators are generated, such as the number of routes, total kilometers traveled, average ideal distance, and additional kilometers per agent. Additionally, 30 replicas were made (reported *4.4.1.1 Replicas*) for VBA (Centralized) and MAS (Distributed), with the purpose of measure the impact of the best and worst solutions, taking into account the indicators reported by the validator. The current airline solution can be found in reported *4.4.1.2 Airline Solution.*

4.4.2. Analysis results

4.4.2.1. Schedule system

Table 4. Scheduling Results per method.

	ALGORITHM		**VBA Solution (Centralized)**		**JADE Solution (Distributed)**	
	Indicators	**Airline Solution**	**Best Solution**	**Worst Solution**	**Best Solution**	**Worst Solution**
Schedule System	**Report**	-	13	24	11	6
	Unattended demand	1434	723	1417	994	1318
	Max Unattended Demand	20	17	17	15	14
	%Penalties	48%	66%	70%	96%	56%
	Activity A-Distribution	33%	23%	10%	16%	14%
	Activity B-Distribution	60%	60%	69%	58%	55%
	Activity C-Distribution	7%	16%	20%	26%	31%
	Activity A-Unattended Demand	12%	24%	66%	52%	46%
	Activity B-Unattended Demand	42%	58%	28%	44%	52%
	Activity C-Unattended Demand	46%	18%	5%	4%	2%
	Schedule Variability	1208.14	724.85	519.69	0	0

It is noticed that in the three solutions using each of the methods (VBA, MAS), the number of unattended demands has a decrease in the two methods concerning the established solution of the airline, but the worst solution for the centralized VBA model resembles the airline's solution. On the contrary, for the distributed MAS model, the best and worst solution manages to maintain and satisfy the demand for scarce human resources in the planned time horizon, which makes the solution report for this method more reliable.

Additionally, the distribution of activities in the MAS model tends to be more homogeneous because the activities are not overloaded as the other two solutions. Consequently, in the distribution of the unattended demand, there are activities that do not need additional personnel, because with the current personnel the unattended demand rate is low, especially, activity C, as shown in *Table 4.*

Finally, the variability in the MAS model presents the value of zero, which shows that the scheduling meets high indicators of employee welfare which means that the initial hour for each shift during the week of planning is constant for each CSA. In contrast, the other solutions, have high values of variability, which can translate into low welfare rates in employees of the airline, leading to employee discomfort.

4.4.2.2. Transport System

Table 5. Transport Results per method.

	ALGORITHM		**VBA Solution (Centralized)**		**JADE Solution (Distributed)**	
Transport System	**Indicators**	**Airline Solution**	**Best Solution**	**Worst Solution**	**Best Solution**	**Worst Solution**
	Additional Km	5.02	7.36	7.53	9.66	6.37
	Average Ideal Distance	10.41	11.15	10.68	10.05	11.35
	Total Km of Routes	5010	3362	3078	3311	4379
	Max Km traveled by agent	-	130.11	88.50	231.43	190.24
	Min Km traveled by agent	-	0.29	0.29	0.02	0.30
	Number of routes	309	144	144	205	274

In this part of the system it can be evidenced as a fundamental criterion that the value of the total kilometers traveled has a better result in the proposed MAS system which decreased approximately 50% to the solution that the airline currently handles, which confirms greater reliability of route scheduling in the proposed MAS environment.

The reason of having better results in the WOSTRA is the optimization that is generated by the algorithm which in its best and worst version decreases the use of vehicles approximately in a third of the solution of the airline and with a significant approach of 50 routes compared to the centralized model in VBA, but even so underneath to the Airline solution.

The average ideal distance for the MAS model presents ideal values of additional km per agent which represents efficient use of vehicles since it is not made use of direct routes but is actually generated routing under the programmed clusters generating greater indirect trips, Compared to the airline, which has a value closer to zero and suggests that most of its routes are direct, which means less efficiency in the generation of routing plans.

It can be verified that the MAS model respects the ideal distances of proximity of the agents of service related to the good results of number of routes and total distance traveled, which makes it too robust a model to have an index almost identical to that of the airline and the centralized model, without penalizing incremental values in transport indices such as: routes and total kilometers traveled.

Figure 10 shows with graphics the solutions report for each model, this figure illustrates the results obtained per indicator such as, schedule variability, demand unattended, total kilometers, number of routes, average ideal distance, and additional Km. Besides illustrates distribution by activities in each model.

Figure 10. Graphs with indicators.

4.4.2.3. Perturbations Scenarios

The first scenario of perturbations is the generation of peaks of demand for any activity; those perturbations could be generated by the user according to their experience. In this case, the perturbations are generated in the same model, but in different activities to determine the reactivity of the system and determine the result of the solution of the agents. The results obtained for this perturbation are showed in *Table 6*.

Table 6. Peak Demand Perturbation.

Perturbation	Description	Result	Human Resources Indicators Before perturbation		Human Resources Indicators After perturbation	
1	There is a lack of 2 more agents at the timeslot 21:30 of the day Monday for activity B	The CSS has 7 proposals and assign those 7 because all of them are idle and to prevent new peaks.	Unattended	1212	Unattended	1214
			Max Unattended	15	Max Unattended	15
			Variability	0	Variability	0
2	There is a lack of 9 agents to the timeslot 14:00 of the day Friday for activity A	The agents 23, 20 and 8 proposes to change and selected by the CSS because at that moment they are in idle state.	Unattended	1193	Unattended	1201
			Max Unattended	15	Max Unattended	15
			Variability	0	Variability	0
3	There is a peak of 7 agents for activity C for the timeslot 00:30 on Sunday.	The agents 20, 59 and 73 are selected because at that moment one of them is not idle, but activity C is more important than the	Unattended	1201	Unattended	1212
			Max Unattended	15	Unattended	15

		current. Also, the other agents are selected because they are idle.	Variability	0	Variability	0

The second scenarios of perturbations are the generation of absent agents for any given day.

Table 7 shows the results of three different scenarios done with this perturbation.

Table 7. Absence Perturbation.

Perturbation	Description	Result	Human resources indicators before perturbation		Human resources indicators before perturbation	
1	A total of 4 agents are said to be absent during the week: - Agent 11 [Fri: 18:00] - Agent 69[Tue: 4:30] - Agent 31[Sat 15:00] - Agent 60[Mon 21:30]	A total of 4 agents were found that are capable to attend the missing demand for the shifts of the absent agents: - Agent 10 instead of 11 - Agent 38 instead of agent 69 - Agent 65 instead of agent 31 - Agent 13 instead of agent 60 All the agents can cover the exact same activities for the previous agents. For transportation, all 4 new agents will need transport and all 4 will travel alone to minimize the impact of the additional km indicator.	Unattended	1300	Unattended	1300
			Max Unattended	14	Max Unattended	14
			Variability	0	Variability	10.48
			Additional Km	7.62	Additional Km	7.62
			Ideal Distance	11.08	Ideal Distance	11.08
2	A total of 3 agents are said to be absent during the week: - Agent 47[Thu 20:30] - Agent 13[Sun 3:30] - Agent 2[Sun 1:30]	A total of 2 agents were found that are capable to attend the missing demand for the shifts of the absent agents: - Agent 51 instead of 47 - Agent 3 instead of agent 13 - For agent 2 there was no available agent to attend the shift All 2 agents can cover the exact same activities for the previous agents. For transportation, the 2 new agents will need transport: - Agent 51 will travel with agent 35 - Agent 3 will travel alone	Unattended	1332	Unattended	1332
			Max Unattended	14	Max Unattended	14
			Variability	0	Variability	11.22
			Additional Km	8.57	Additional Km	8.47
			Ideal Distance	11.2	Ideal Distance	11.22
3	A total of 4 agents are said to be absent during the week: - Agent 35 [Fri: 3:00] - Agent 31 [Mon: 2:00] - Agent 66 [Tue 16:30] - Agent 58 [Vie 20:00]	A total of 4 agents were found that are capable to attend the missing demand for the shifts of the absent agents: - Agent 70 instead of 35 - Agent 35 instead of agent 31 - Agent 56 instead of agent 56 - Agent 4 instead of agent 58 All the agents can cover the exact same activities for the previous agents. For transportation, all 4 new agents will need transport and all 4 will travel alone to minimize the impact of the additional km indicator.	Unattended	1182	Unattended	1182
			Max Unattended	14	Max Unattended	14
			Variability	0	Variability	10.73
			Additional Km	7.07	Additional Km	6.98
			Ideal Distance	10.71	Ideal Distance	10.73

It is worth clarifying the importance of reactivity for the results obtained in the six perturbations performed. This is because in the solutions found there was a high level of interaction, communication and cooperation between the agents and their supervisor, responding to changes that occurred, while maintaining the feasibility of the solution, in addition to reacting quickly and with low complexity, with estimated times of less than a second to obtain a new feasible solution to any given perturbation. This low complexity is given by the cooperation and communication between agents, and the distributed environment in which they work, contrary to the VBA complexity, which is much higher given that there is no distributed environment and the whole model would be needed to be ran from the start in order to accomplish the perturbations, making the generation of a new solution with modifications to last between 15-20 minutes.

5. Conclusions

To conclude this work, several positive aspects can be highlighted in the use of MAS that allows the airline to be more competitive in the market and improve its customer service. First, the algorithmic complexity to find a feasible solution of the proposed MAS system is reduced considerably compared to a centralized system, due to the characteristics of agents that facilitates the solution of a complex model, as well as reacting to unexpected events. Secondly, the proposed system focuses mainly on meeting passengers' demand that exists for each customer service agent; however, it also focuses on the well-being of those who serve the demand, both in scheduling and transportation.

For this reason, it was decided as a requirement for the solution of the problem, that all agents had a fixed entry time and the same distribution of activities for every day during the planning horizon, which compared to the information provided by the airline and the centralized solution, generates better solutions in terms of well-being and therefore could generate a positive impact to employees, improving their welfare and job satisfaction. As mentioned above, the system also focuses on the welfare of agents in the transport section. It was decided to give more priority to the welfare of agents than to the efficiency of the routes established by the airline, so that agents did not have to make so many indirect journeys and traveled fewer kilometers on the planning horizon.

Also, the system allows simulating unexpected changes in the environment of the airline, for this reason, the agents perceive those changes and decide rapidly without significant impact on the indicators, such as, non-attended demand and ideal kilometer increasing in less of 1%, owing to, the design of agents that focus on distributing the decision-making process dividing indicators per department of the airline.

As future work, the system could be better used by coupling the system to an information system that provides data to agents in order for them to learn about them and make better decisions for the purpose of the organization. As well, the airline could add more perturbances scenarios that focus more on their needs, to which the system can adapt and give more flexibility to the changes in the environment.

Finally, as a recommendation to the airline, it is important to offer training to CSA in Activity A, since according to most of the results of the methods, this activity is the one with the highest percentage of demand dissatisfaction, hence, there are not many agents who can carry out this activity.

6. Glossary

Agent: Computer systems capable of carrying out actions autonomously in some environment, to achieve a series of objectives.

Expressiveness: Are the models of the methodology capable of representing the system from different perspectives, capturing all necessary aspects such as static and dynamic aspects, and system- and agent-level aspects.

Modularity: Do the methodology and its models promote modularity in the design of agents and the system.

Autonomy: Can the models support and represent the autonomous feature of agents (i.e., the ability to act without the direct intervention of humans or others, and to control their states and behavior).

Adaptability: Can the models support and represent the adaptability feature of agents (i.e., the ability to learn and improve with experience).

Cooperative behavior: Can the models support and represent the cooperative behavior of agents (i.e., the ability to work together with other agents to achieve a common goal).

Reactivity: Can the models support and represent the reactivity of agents (i.e., the ability to selectively sense and act promptly).

7. References

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