Oct 27th, 1:30 PM - 3:00 PM

Simulation Based Optimisation of Ground Crews: Case of a Regional Airport

Blaz Rodic
Faculty of Information Studies, blaz.rodic@fis.unm.si

Alenka Baggia
University of Maribor, alenka.baggia@fov.uni-mb.si

Recommended Citation

Rodic, Blaz and Baggia, Alenka, "Simulation Based Optimisation of Ground Crews: Case of a Regional Airport" (2018). *UBT International Conference*. 109.
https://knowledgecenter.ubt-uni.net/conference/2018/all-events/109

Simulation Based Optimisation of Ground Crews: Case of a Regional Airport

Blaz Rodic [1], Alenka Baggia[2]

[1] Faculty of Information Studies, Ljubljanska cesta 31a, Novo Mesto, Slovenia Blaz.Rodic@fis.unm.si

[2] Faculty of Organizational Sciences, University of Maribor, Kidriceva cesta 55a, Kranj, Slovenia Alenka.Baggia@fov.uni-mb.si

Abstract. Paper presents the simulation models built within an airport ground crew scheduling automatization project at a regional airport. Our goal was to develop robust ground crew task scheduling and shift generation algorithms that would improve on existing heuristic rules. We have utilized simulation modeling to develop and validate the algorithms, starting with a model of the existing scheduling process coded and visualized in spreadsheet software and ending with a hybrid Discrete Event and Agent Based model used for the visualization and verification of the optimized processes. Explicit and tacit expert knowledge was recorded through meetings with airport personnel managers and observation of the ground crew processes. Gathered knowledge was combined with business rules, contractual limitations and labor legislation to develop the final version of the algorithms.

Keywords: personnel scheduling, airport ground crews, simulation modelling, optimization

1 Introduction

In the last decade, global air traffic passenger demand has steadily increased. According to the ACI Europe report [1] the fastest passenger traffic growth (8.5%) in 13 years was reported during 2017. On a global scale, passenger air travel is expected to maintain positive growth rates up to 2030, despite a number of challenges faced by the industry. Between 2017 and 2036, the number of airline passengers is expected to grow at a compound annual growth rate (CAGR) of 4.7 percent [2].

Due to increased air traffic, airports as well as airlines are facing diverse challenges in ensuring efficient, high quality services while generating profit [3–9].

While airlines cater to passenger, airports provide services to airlines as well. One of the challenges that airports face is the optimization of labor and equipment of ground crews [10, 11]. Passengers expect comfort, efficiency and safety, while airlines seek to reduce costs and require efficient and adaptable ground services.

Airports processes are complex and overlapping, with frequent changes due to changes in flight schedules, making their optimization a mathematically and empirically difficult task. The handling of an aircraft from the time it arrives at the gate, to the time of the departure for the next flight, has to be performed quickly, efficiently and accurately to minimize flight delays and provide a valuable service for the airline and the passengers [12–14], requiring efficient ground crew management and training [15].

A comprehensive overview of scheduling and simulation modelling methods and tools for airport and airline operations optimization is presented in [16] and [17]. Airport ground crew scheduling solution mostly focus on partial scheduling solutions for individual task types, e.g. baggage handling [18], check-in [19, 20], runway scheduling and ground movement [14, 21, 22] or security tasks [23].

1.1 Ground Crew Operations

Every flight arriving or departing from the airport requires the execution of a series of tasks. Which tasks are required per flight, in what sequence, how many workers and what equipment is required, etc. is defined by heuristics specified by the airlines and airport business rules. Tasks can be performed only by groups of airport personnel (henceforth work groups), with suitable skills. Further details on the heuristics are omitted in this paper due to space limitations, but can be found in [24].

1.2 Literature review

Discrete Event Simulation (DES) is often combined with heuristic scheduling methods for ground operations optimization [25]. However, the relative rigidity of DES model makes it less suitable for modelling of complex socio-technical systems. Agent based modelling (ABM) is better suited for modelling of complex systems, and is thus often used to supplement or replace DES in recent research, [12, 26, 27]. Combining DES and ABM allows researchers to model stable, static processes using DES, using ABM, which is more difficult to implement, only for the dynamic processes, where a DES model would be too complex or infeasible to implement [6, 12, 16, 25–30].

2 Methodology and Results

2.1 Airport Model

According to available data, we have identified the DES as the base method to model the aircraft traffic simulation model, and decided to supplement it with ABM elements to model the processes and movement of ground crews. Using ABM, we can lower the level of abstraction to improve insight into the ground crew operations and making the simulation presentation more transparent for the airport management.

The air traffic model (Figure 1) consists of two submodels: the *Arrivals* submodel, and the *Departures* submodel. This reflects the airport business rules and available flight schedule data: FIS does not track individual aircraft as they transition from “arrival” to “departure”.

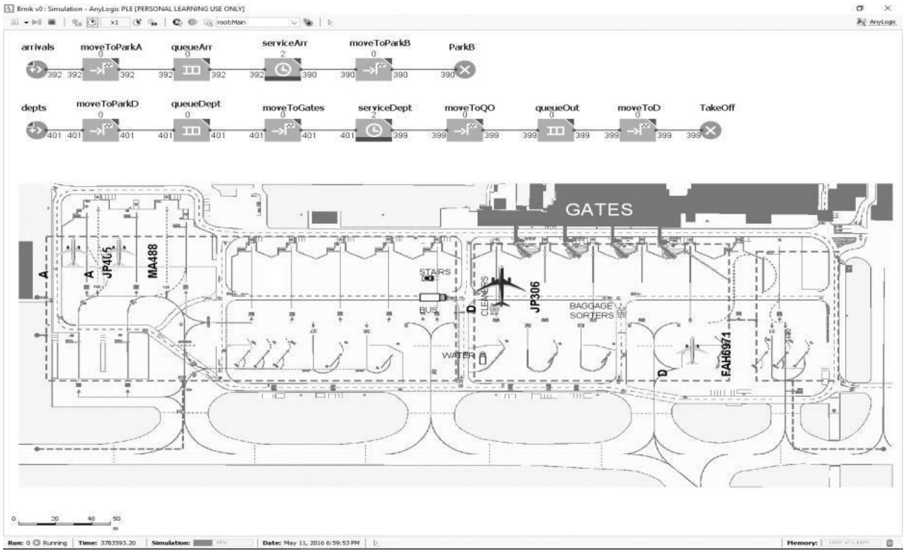

Figure 1: Main view of the simulation model with DES air traffic model and airport layout.

The arrivals submodel is linked with a spreadsheet containing the arrival schedule from FIS and the scheduling heuristics database, which allows it to introduce (create) aircraft into the model at modeled arrival time. Aircraft are modelled as agents that pass through the DES model, while the aircraft’s graphical representation moves through the 2D model of the airport. Aircraft taxi to the gates (*moveToParkA* and *queueArr*) or wait on the apron for gate assignment. The submodel of arrivals ends with an element modeling transition to airport parking, which removes aircraft point from the model. Conversely the *Departures* model introduces the aircraft into the model at the exit from airport parking. We assume that the departing aircraft is present at the airport and available to ground crews.

The departure tasks start times are based on the departure times given in the FIS schedule. The modelled departure times depend on the execution of tasks and should not be delayed when scheduling constraints are defined properly. In the *Departures* submodel an aircraft first has to move to the gates (elements *moveToParkD*, *queueDept* and *moveToGates*), where it is serviced (e.g. boarded by passengers, loaded with baggage, etc.), with the delay modelled with ServiceDept element. Afterwards, the aircraft moves to the runway (*moveToD*, *TakeOff*). The queues were modelled to enable the simulation of an aircraft waiting until a taxiway or a gate or a parking area is available.

FIS data is transferred from a spreadsheet into an internal (AnyLogic) database, and transferred to the DES model initial elements arrivals and depts. The ground crew tasks requirements are transferred to every aircraft agent at the moment of its entry in the model and stored in agent's internal data structure for easy accessibility. In turn, the aircraft forwards the relevant ground crew task requirements to suitable work group in a service request message. Work group agents maintain an internal queue of tasks, which are executed according to the FIFO (first-in first-out) rule and specified service start time.

4.3 Ground Crew Model

Work groups are modelled as agents using the same internal state chart model of its task process as shown in Figure 2, however each agent states and variables change independently, allowing modelling of autonomous behavior and making each agent a submodel within the airport model.

After creation of an agent, its initial state is Waiting: agent waits for a message containing a service request and specifying tasks to be executed (i.e. number of personnel, desired start of service, desired end of service). Service requests are stored in an agent's internal queue and processed according to FIFO rule. If an agent is in the Waiting state (i.e. free), a request is queued, and model time equals the specified task start time, the work group agent moves to the aircraft, begins the requested task, and performs it until specified task end time. After the task is complete, the work group agent sends a message to the aircraft and proceeds to the next aircraft in its internal queue or returns to the waiting area.

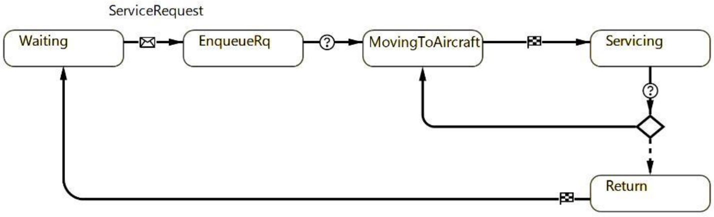

Figure 2: State chart of the ABM of a ground crew group.

5 CONCLUSION

Our goal was to develop robust ground crew scheduling and shift generation algorithms that would improve on existing heuristic rules developed gradually by the company experts, and implement them in an application that would be integrated with the airport's human resource management software. Simulation and modelling was used develop and verify the algorithms, starting with an existing scheduling process model coded and visualized in a spreadsheet and ending with a hybrid DES and ABM model used for the visualization and verification of the optimized processes. Gathered knowledge was combined with business rules, contractual limitations and labor legislation to develop the final version of the algorithms.

We can conclude from our experience in this project that scheduling problems in the air transport industry are significantly different from traditional machine scheduling problems, as the mathematical scheduling models from previous research could not be utilized, and heuristic algorithms had to be developed instead.

As the heuristic rules are largely recorded in the database, the developed scheduling automatization solution is flexible, and can be adapted as the airport is enlarged, carriers and their requirements change, etc., as long as the changes affect only the data that the algorithms use: the criteria, their priorities, and their values.

The optimization implemented in the algorithms is limited by the possibilities for transition of workers between tasks and the criteria defining the workforce requirements per tasks. A more detailed task and skill categorization, and a more detailed differentiation between the requirements of different aircraft types and airlines would allow a more precise workforce requirement and task timing criteria and thus a better optimization of workforce requirements.

REFERENCES

1. ACI Europe: 2017 - a Vintage Year With Air Passenger Traffic Growth of 8 . 5 %. 8–11 (2018).
2. Statista: Annual growth in global air traffic passenger demand from 2005 to 2018, http://www.statista.com/statistics/193533/growth-of-global-air-traffic-passenger-demand/.
3. Bian, F., Burke, E., Jain, S., Kendall, G.: Measuring the robustness of airline fleet schedules. In: Kendal, G., Burke, E., Petrovic, S., and Gendreau, M. (eds.) Multidisciplinary scheduling: theory and applications. pp. 381–392. Springer Science + Business Media, New York (2005).
4. Burke, E.K., De Causmaecker, P., De Maere, G., Mulder, J., Paelinck, M., Vanden Berghe, G.: A multi-objective approach for robust airline scheduling. Comput. Oper. Res. 37, 822– 832 (2010).
5. European Organisation for the Safety of Air Navigation: Standard Inputs for EUROCONTROL Cost-Benefit Analyses. , BRUSSELS (2015).
6. Gurtner, G., Bongiorno, C., Ducci, M., Miccichè, S.: An Empirically grounded Agent Based simulator for the Air Traffic Management in the SESAR scenario. (2016).
7. El Moudani, W., Mora-Camino, F.: A dynamic approach for aircraft assignment and maintenance scheduling by airlines. J. Air Transp. Manag. 6, 233–237 (2000).
8. Weiszer, M., Chen, J., Locatelli, G.: An integrated optimisation approach to airport ground operations to foster sustainability in the aviation sector. Appl. Energy. 157, 567–582 (2014).
9. Yan, S., Tang, C.H., Fu, T.C.: An airline scheduling model and solution algorithms under stochastic demands. Eur. J. Oper. Res. 190, 22–39 (2008).
10. Clausen, T.: Airport ground staff scheduling, (2011).
11. Zeng, L., Zhao, M., Liu, Y.: Airport ground workforce planning with hierarchical skills: a new formulation and branch-and-price approach. Ann. Oper. Res. 1–14 (2017).
12. García Ansola, P., García Higuera, A., Pastor, J.M., Otamendi, F.J.: Agent-based decision-making process in airport ground handling management. Logist. Res. 3, 133–143 (2011).
13. Gomez, F., Scholz, D.: Improvements to Ground Handling Operations and their Benefits to Direct Operating Costs. Dtsch. Luft- und Raumfahrtkongress. 1–11 (2009).

14. Weiszer, M., Chen, J., Stewart, P.: Preference-Based Evolutionary Algorithm for Airport Runway Scheduling and Ground Movement Optimisation. IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC. 2015–Octob, 2078–2083 (2015).
15. De Bruecker, P., den Bergh, J., Belien, J., Demeulemeester, E.: A two-stage mixed integer programming approach for optimizing the skill mix and training schedules for aircraft maintenance. In: International Conference on Operations Research. , Aachen (2014).
16. Herbers, J.: Models and Algorithms for Ground Staff Scheduling on Airports, (2005).
17. Bazargan, M.: Airline Operations and Scheduling. Ashgate Publishing Limited, Aldershot (2004).
18. Chu, S.C.K.: Generating, scheduling and rostering of shift crew-duties: Applications at the Hong Kong International Airport. Eur. J. Oper. Res. 177, 1764–1778 (2007).
19. Lin, D., Xin, Z., Huang, Y.: Ground Crew Rostering for the Airport Check-In Counter. In: 2015 IEEE International Conference on Industrial Engineering and Engineering Management. pp. 2–6. , Singapore (2015).
20. Stolletz, R.: Operational workforce planning for check-in counters at airports. Transp. Res. Part E Logist. Transp. Rev. 46, 414–425 (2010).
21. Bennell, J.A., Mesgarpour, M., Potts, C.N.: Airport runway scheduling. 4OR. 9, 115–138 (2011).
22. Soomer, M.J., Franx, G.J.: Scheduling aircraft landings using airlines' preferences. Eur. J. Oper. Res. 190, 277–291 (2008).
23. Abdoul Soukour, A., Devendeville, L., Lucet, C., Moukrim, A.: A Memetic Algorithm for staff scheduling problem in airport security service. Expert Syst. Appl. 40, 7504–7512 (2013).
24. Rodic, B., Baggia, A.: Airport Ground Crew Scheduling Using Heuristics and Simulation. In: Mujica Mota, M. and Flores de la Mota, I. (eds.) Applied Simulation and Optimization 2: New Applications in Logistics, Industrial and Aeronautical Practice. pp. 131–160. Springer International Publishing AG (2017).
25. Piera Eroles, M.À., Ramos, J.J., Fernandez Robayna, E.: Airport Logistics Operations. In: Merkuryev, Y., Merkuryeva, G., Piera, À.M., and Guasch, A. (eds.) Simulation-Based Case Studies in Logistics: Education and Applied Research. pp. 209–228. Springer London, London (2009).
26. Bouarfa, S., Blom, H., Curran, R.: Agent-Based Modeling and Simulation of Coordination by Airline Operations Control. IEEE Trans. Emerg. Top. Comput. 4, 1–1 (2016).
27. Peng, Y., Wei, G., Junqing, S., Bin, S.: Evaluation of Airport Capacity through Agent Based Simulation. Int. J. Grid Distrib. Comput. 7, 165–174 (2014).
28. Kleinman, N.L., Hill, S.D., Ilenda, V.A.: Simulation optimization of air traffic delay cost. In: Proceedings of the 1998 Winter Simulation Conference. pp. 1177–1181. , Washington DC (1998).
29. Mujica Mota, M., Scala, P., Delahaye, D.: Improving Airport Performance Through a Model-Based Analysis and Optimization Approach. Appl. Simul. Optim. 2 New Appl. Logist. Ind. Aeronaut. Pract. 109–129 (2017).
30. Sabar, M., Montreuil, B., Frayret, J.M.: An agent-based algorithm for personnel shift-scheduling and rescheduling in flexible assembly lines. J. Intell. Manuf. 23, 2623–2634 (2012).